

IBN HALDUN UNIVERSITY
SCHOOL OF GRADUATE STUDIES
DEPARTMENT OF AIR TRANSPORT MANAGEMENT

MASTER THESIS

**THE IMPACT OF OPERATIONAL PERFORMANCE OF
FULL-SERVICE CARRIER AIRLINES ON STOCK
PRICES DURING COVID-19**

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ISTANBUL, 2025

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PRICES DURING COVID-19**

**by
HAMZA APAYDIN**

**A thesis submitted to the School of Graduate Studies in partial
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ISTANBUL, 2025

ACADEMIC HONESTY ATTESTATION

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ÖZ

COVID-19 DÖNEMİNDE TAM SERVİS HİZMET VEREN HAVAYOLLARININ OPERASYONEL PERFORMANSININ HİSSE SENEDİ FİYATLARINA ETKİSİ

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COVID-19 pandemisi, havacılık sektöründe ani bir şok etkisi yaratmıştır. Sokağa çıkma yasakları ve ülke sınırlarının kapanması ile birlikte yolcu sayılarında ve operasyonel verilerde tarihi bir düşüş yaşanmıştır. Bu çalışmada, COVID-19 pandemisi sürecinde ve sonrasında tam hizmet sağlayan havayolu şirketlerinin operasyonel performans göstergelerinin hisse senedi fiyatlarına etkisi incelenmektedir. 2019 ile 2024'ün üçüncü çeyreği arasındaki döneme ait Türk Hava Yolları, Lufthansa ve American Airlines'a ait aylık veriler kullanılmıştır. Seçilen bu havayolları sırasıyla Türkiye, Avrupa ve ABD'deki tam servis sağlayan havayollarını temsil etmektedir. Çalışmada bu havayollarına ait, Uçuş Koltuk Kilometresi (ASK), Ücretli Yolcu Kilometresi (RPK), Doluluk Oranı (LF), Yolcu Sayısı (PN) ve Uçuş Sayısı (FN) gibi operasyonel performans göstergelerinin hisse fiyatlarına etkisi analiz edilmiştir. Veriler R yazılımı ile panel veri ve zaman serisi ekonometrik modelleri kullanılarak incelenmiştir. Çalışma neticesinde, operasyonel performans göstergelerinden doluluk oranının (LF), COVID-19 döneminde, seçilen havayolları için hisse senedi fiyatları üzerinde pozitif ve istatistiksel olarak anlamlı bir etkisinin olduğu tespit edilmiştir. Diğer operasyonel performans göstergeleri için, hisse senedi fiyatları üzerinde herhangi anlamlı bir etki bulunamamıştır. Ayrıca, pandemi döneminde incelenen havayolu şirketlerinin hisse fiyatlarının geçmiş değerlerinden güçlü şekilde etkilendiği görülmüştür. Bunun nedeninin COVID-19'un makroekonomik etkilerinin yatırımcılar üzerinde oluşturduğu yatırım algısı olduğu düşünülmektedir. Çalışmada elde edilen bir diğer sonuç ise, COVID-19 pandemisinin hisse senedi fiyatları üzerindeki etkisinin

kısa vadeli olduđu ve uzun vadede istatistiksel olarak kalıcı ve anlamlı bir etkisinin olmadığıdır. Ayrıca verilerin incelenmesi sonucunda, operasyonel performans göstergelerinin incelenen bütün havayolları için COVID-19'un başlamasıyla birlikte bir kırılım yaşadığı ve ani şekilde düştüğü görülmüştür. Sonrasında ise bu göstergelerin incelenen her havayolu için toparlanması farklı boyutlarda olmuştur. Lufthansa'nın göstergeleri pandemi öncesindeki seviyelerine ulaşamamış, American Airlines'ınkiler pandemi öncesi seviyelerini yakalayabilmiş, Türk Hava Yolları'nın göstergeleri ise pandemi öncesi seviyelerini önemli ölçüde geçmiştir. Hisse senedi fiyatlarına bakıldığında, Lufthansa ve American Airlines'ın hisse senedi fiyatlarının COVID-19 öncesi fiyatlarına geri dönmekte zorlandığı, Türk Hava Yolları'nın ise pandemi öncesi değerlerini geçip önemli ölçüde olumlu ayrıştığı gözlemlenmiştir.

Anahtar Kelimeler: Covid-19, Finans, Hisse Senedi Fiyatı, Operasyonel Performans, Ticari Havacılık, Yönetim Muhasebesi.

ABSTRACT

THE IMPACT OF OPERATIONAL PERFORMANCE OF FULL-SERVICE CARRIER AIRLINES ON STOCK PRICES DURING COVID-19

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The COVID-19 pandemic was a sudden shock to the aviation industry. Home lockdowns and the closure of national borders caused a historic drop in passenger numbers and operational indicators. This study examines how the operational performance indicators of full-service airline companies affected their stock prices during and after the COVID-19 pandemic. Monthly data from 2019 to the third quarter of 2024 were collected for Turkish Airlines, Lufthansa, and American Airlines, representing full-service airlines in Türkiye, Europe, and the USA. The analysis focuses on the effects of operational performance indicators, such as Available Seat Kilometers (ASK), Revenue Passenger Kilometers (RPK), Load Factor (LF), Passenger Numbers (PN), and Flight Numbers (FN) on stock prices. The data were analyzed using panel data and time series econometric models with R software. The findings reveal that the load factor (LF) operational performance indicator has a positive and statistically significant effect on stock prices during the COVID-19 period for the selected airlines, while the other indicators had no effect. In addition, it was found that the stock prices of these airlines were strongly influenced by their past values during the pandemic. This may be due to the perception of investors created by the pandemic's macroeconomic effects. Another result of the study is that the impact of the pandemic on stock prices was only short-term and did not have a statistically significant impact in the long term. The data also indicate that the operational performance indicators of all the examined airlines experienced a sudden drop at the beginning of the pandemic. However, the recovery levels varied among the airlines.

Lufthansa's indicators did not return to pre-pandemic levels, while American Airlines managed to reach them. Turkish Airlines significantly surpassed its pre-pandemic operational levels. Regarding stock prices, it was observed that Lufthansa and American Airlines struggled to recover their pre-COVID values. At the same time, Turkish Airlines stood out by exceeding them and showed a substantial positive upward divergence.

Keywords: Aviation, Finance, Operational Performance, Stock Prices, Covid-19, Managerial Accounting.



DEDICATION

It is dedicated to my beloved Wife and Mom.



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I want to thank my wife for her support during my studies. I also want to thank my advisor, Prof. Tamer Aksoy, for leading me throughout the research and writing of my thesis.

Hamza Apaydın

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TABLE OF CONTENTS

ÖZ	iv
ABSTRACT	vi
DEDICATION.....	viii
ACKNOWLEDGEMENT.....	ix
TABLE OF CONTENTS.....	x
LIST OF TABLES	xii
LIST OF FIGURES	xiii
LIST OF SYMBOLS AND ABBREVIATIONS	xiv
CHAPTER I INTRODUCTION.....	1
CHAPTER II CIVIL AVIATION AND AIRLINE SECTOR.....	5
2.1. Civil Aviation	5
2.2. Airline Sector	5
2.2.1. Historical Evolution of the Airline Sector.....	7
2.2.2. Airline Sector in Türkiye.....	10
2.2.3. Specifications of Airline Product	12
2.2.4. Sector-Specific Properties of the Airline Sector	14
2.2.5. Classification of Airline Companies	14
2.2.5.1. Full-Service Carriers	15
2.2.5.2. Low-Cost Carriers	15
2.2.5.3. Regional Airlines.....	16
2.2.5.4. Charter Airlines	16
2.2.5.5. Cargo Airlines	16
CHAPTER III PERFORMANCE INDICATORS OF AIRLINE COMPANIES...	17
3.1. Performance Measurement in Companies.....	17
3.2. Performance Indicators of Airline Companies	17
3.3. Financial Indicators of Company Stocks.....	18
3.3.1. Stock Price.....	20
3.3.2. Earnings Per Share	20
3.3.3. Price/Earnings (P/E) Ratio	21
3.3.4. Market Value to Book Value (P/B) Ratio	21
3.4. Operational Performance Indicators of Airline Companies	22
3.4.1. Available Seat Kilometers.....	22
3.4.2. Revenue Seat Kilometers	27
3.4.3. Load Factor.....	28

3.4.4. On-Time Performance	29
3.4.5. Utilization of Aircraft	29
3.5. Relationship between Operational Performance Indicators and Financial Performance Indicators of Airline Companies	30
CHAPTER IV EFFECT OF GLOBAL EXTERNAL SHOCKS ON AIRLINE COMPANIES' PERFORMANCE AND COVID-19	34
4.1. Global External Shocks	34
4.1.1. 1970s Petrol Crisis.....	41
4.1.2. 1997 Asia Financial Crisis	41
4.1.3. 2001 9/11	42
4.1.4. 2003 SARS	42
4.1.5. 2008 Global Financial Crisis.....	43
4.1.6. COVID-19	43
CHAPTER V THE IMPACT OF PERFORMANCE OF FULL-SERVICE CARRIER AIRLINES ON STOCK PRICES DURING COVID-19	53
5.1. Subject and Purpose of the Research	53
5.2. Importance of the Research	53
5.3. Restrictions of the Research	54
5.4. Literature Review	56
5.5. Data Set	63
5.6. Descriptions of the Variables Used in the Econometric Model	64
5.7. Research Model.....	65
5.8. Hypothesis of the Research	66
5.9. Methodology	66
5.10. Empirical Findings	68
5.10.1. Time Series Analysis.....	80
5.10.1.1. American Airlines Time Series Analysis	83
5.10.1.2. Lufthansa Time Series Analysis.....	88
5.10.1.3. Turkish Airlines Time Series Analysis.....	93
5.11. Discussion	99
CHAPTER VI CONCLUSION AND SUGGESTIONS	102
REFERENCES.....	106
CURRICULUM VITAE.....	117

LIST OF TABLES

Table 2.1. Top Busiest Airports in Europe in 2024	12
Table 5.2. Variables Used in the Analysis	64
Table 5.3. Results of Unit Root Tests	74
Table 5.4. Multicollinearity Test of Independent Variables	75
Table 5.5. Testing the Presence of Heteroskedasticity and Serial Autocorrelation ...	76
Table 5.6. Balanced Panel Model Analysis Using the Fixed-Effects Model.....	77
Table 5.7. Dynamic Panel Model.....	79
Table 5.8. American Airlines Stationery Tests	83
Table 5.9. Ridge Regression Model Estimation Results for American Airlines	85
Table 5.10. ARDL Model Estimation Results for American Airlines	86
Table 5.11. UECM Model Estimation Results for American Airlines	87
Table 5.12. RECM Estimation Results for American Airlines.....	88
Table 5.13. Lufthansa Stationery Test	89
Table 5.14. Ridge Regression Model Estimation Results for Lufthansa	91
Table 5.15. ARDL Model Estimation Results for Lufthansa.....	91
Table 5.16. UECM Model Estimation Results for Lufthansa.....	92
Table 5.17. RECM Estimation Results for Lufthansa.....	93
Table 5.18. Stationarity Tests for Turkish Airlines.....	94
Table 5.19. Ridge Regression Model Estimation Results for Turkish Airlines.....	96
Table 5.20. ARDL Model Estimation Results for Turkish Airlines	96
Table 5.21. UECM Model Estimation Results for Turkish Airlines	97
Table 5.22. RECM Estimation Results for Turkish Airlines	98
Table 5.23. Results of Hypothesis Tests	99

LIST OF FIGURES

Figure 2.1. Number of Passengers in the Airline Industry 2004-2024 (Millions)	10
Figure 3.1. Emirates Route Map	24
Figure 3.2. Wideroe Route Map	26
Figure 4.1. British Airways Route Change After Russian Airspace Closure	38
Figure 4.2. World Passenger Traffic Evolution 1945-2022	44
Figure 4.3. Eurocontrol Actual and Future Traffic Count in Millions	49
Figure 4.4. Passenger Numbers of Selected Airlines Compared to 2019	51
Figure 5.1. Trend of ASK	68
Figure 5.2. Trend of RPK	69
Figure 5.3. Trend of PAX	70
Figure 5.4. Trend of FN	71
Figure 5.5. Trend of LF	72
Figure 5.6. Trend of SP	73
Figure 5.7. Correlation of Variables	75
Figure 5.8. Decomposition Analysis of American Airlines	81
Figure 5.9. Decomposition Analysis of Lufthansa	81
Figure 5.10. Decomposition Analysis of Turkish Airlines	82

LIST OF SYMBOLS AND ABBREVIATIONS

ASK	Available Seat Kilometers
RPK	Revenue Passenger Kilometers
THY	Turkish Airlines
FN	Flight Number
PAX	Passengers
PN	Passenger Number
SP	Stock Price
LF	Load Factor
LHA	Lufthansa
AAL	American Airlines
VIF	Variance Inflation Factor
GMM	Generalized Method of Moments
ARDL	Autoregressive Distributed Lag
UECM	Unrestricted Error Correction Model
RECM	Restricted Error Correction Model
HAC	Heteroskedasticity and Autocorrelation Consistent
ADF	Augmented Dickey-Fuller
ECT	Error Correction Term

CHAPTER I

INTRODUCTION

As key units within economies, businesses substantially affect societal welfare and economic development. Employment provided by businesses leads to an increase in income levels for employees. This increased income is then transferred to other economic sectors, resulting in broader economic activity and productivity. Businesses enhance economic value and contribute to the overall welfare of societies. These multiple contributions make them indispensable elements of modern economies.

Interruptions in business operations can negatively affect both economic and social systems. These negative effects include unemployment, economic contraction, and decreases in income levels. These challenges highlight the critical role businesses play in maintaining the stability and growth of societies.

Measuring the performance of businesses is crucial for understanding whether they are functioning healthily or not. This measurement employs various financial and operational indicators to assess a business's current state, success, and sustainability. Evaluating a company's performance is significant for employees, managers, governments, and investors, as it provides essential insights into the efficiency and potential areas of improvement within the business. This process ensures that stakeholders have a clear view of the company's health and future.

Operational indicators play a significant role in measuring business performance. These indicators provide valuable insights into a company's activities' effectiveness, efficiency, and overall operational success. Industry-specific performance metrics enable comparison between a company and its peers within the same industry, which guides managers in the strategic decision-making process. By evaluating operational indicators, managers can identify areas of strength and opportunities for improvement.

This helps them to align operational strategies with business objectives to enhance competitiveness and business performance.

Airline companies, fundamentally service enterprises, play crucial roles economically and socially within societies. These companies offer the rapid and efficient transportation of people and goods across geographical regions, thereby supporting and stimulating global economic activities. Airlines contribute to the growth of sectors such as tourism and trade, thus generating a broader economic impact. This ability to bridge major distances quickly enhances global connectivity and boosts local economies by increasing accessibility to international markets and tourism revenues.

There is a close relationship between company performance and stock prices. Generally, a company's profitability and revenue growth positively influence its stock prices, as investors are interested in companies with higher future earnings potential. Stock prices are influenced by current financial performance, market expectations, and perceptions of the company's future performance. Investors' positive or negative expectations about the company can significantly affect its stock prices. Developments within an industry can also impact the stock prices of companies within that sector. Technological innovations, regulatory changes, or sectoral crises can affect the performance of relevant companies, thus affecting their stock prices.

External shocks are unexpected events that occur outside the control of businesses and often come from economic, political, natural, or health-related developments. These events can significantly impact businesses; they can decrease sales, disrupt supply chains, increase operational costs, and affect overall business strategies.

For airlines, external shocks can include fluctuations in oil prices, geopolitical events, natural disasters, or pandemics. Such shocks can lead to a decrease in demand, flight cancellations, revenue loss, and operational difficulties, which can negatively impact airline companies' financial health and market position. These events require robust risk management and contingency planning to decrease their significant effect on the business and ensure the continuity of operations under challenging circumstances.

COVID-19 is a respiratory disease caused by the SARS-CoV-2 virus, which first emerged in Wuhan, China, in December 2019. The disease spread rapidly worldwide, causing the World Health Organization (WHO) to declare a pandemic in March 2020. During the pandemic, countries implemented various precautions such as quarantine, social distancing, closing borders, and mask wearing to control the spread of the virus (Sohrabi et al., 2020).

COVID-19 has had a historic impact on the aviation industry, far more deeply and globally than previous external shocks such as the 9/11 attacks, the 2008 economic crisis, or the oil crises. The pandemic led to widespread travel restrictions, sharp declines in air traffic, and the closure of international borders, severely affecting the industry. Unlike other shocks that affected specific regions or operational aspects, COVID-19 brought global aviation to a near halt and necessitated the development of new strategies for recovery. (Chinazzi et al., 2020).

The recovery process for airline companies after the COVID-19 pandemic has varied significantly. While some airlines have quickly recovered due to eased travel restrictions and rising passenger demand, others are still struggling to reach their pre-pandemic levels. This uneven recovery reflects the different impacts of the pandemic across various regions and market segments, as well as the varying effectiveness of recovery strategies implemented by individual airlines. In the meantime, due to these differences, stock prices performed differently between airline companies, resulting in some bringing significant losses, and some important gains (Carter et al., 2022).

This study aims to examine the impact of operational performance indicators of full-service airlines on their stock prices during and after the COVID-19 pandemic. The analysis was conducted on full-service airlines, including Turkish Airlines (THY), Lufthansa (LHA), and American Airlines (AAL), with monthly operational data between 2019 and 9M2024.

Previous research, such as that by Riley et al. (2003), Turturea & Turcu (2015), Alici (2020), and Samson (2021) used data that ended in 2020, which leaves a gap in addressing the post-COVID-19 period. The purpose of this study is to fill this gap. This information is intended to be valuable to academics, investors, managers, and

industry representatives. By providing up-to-date data, this research aims to assist in making informed decisions within the industry.

The study utilizes panel data and time series econometric analysis using the R 4.4.2 program. First, the panel data analysis is done for all the aforementioned airlines. A time series analysis is then implemented for these airlines individually. An econometric model is formed using ASK, RPK, LF, FN, PN as independent variables and stock price as a dependent variable. Also, a dummy variable for the COVID-19 period was included in the model. The data is collected from the annual reports, investor relations web page of the airlines, and from the United States Department of Transportation (DOT)'s Transportation Data website.

For panel data analysis, Levin-Lin-Chu unit root tests, Breusch-Pagan and Breusch-Gofrey tests, Sargan tests, Wald tests, and VIF tests are implemented. Panel-Ridge regression, Arellano-Bond, and Blundell-Bond models are used. For time series analysis, ADF unit root test, Bai-Perron tests, Jarque-Bera tests, and Decomposition tests are done. ARDL, UECM, and RECM models are used in the study.

The study is organized into six main sections: The introduction sets the stage for the research. The second section provides an overview of the airline industry. The third section reviews specific performance metrics unique to the airline sector. The fourth section explores external shocks that have historically impacted the airline industry, with a particular focus on the COVID-19 pandemic. The fifth section covers the literature review, details of the research methodology, and analysis of the findings. The study concludes with a final section summarizing the outcomes and recommendations.

CHAPTER II

CIVIL AVIATION AND AIRLINE SECTOR

2.1. Civil Aviation

The civil aviation sector consists of all non-military air transportation activities. This broad industry includes passenger and cargo transportation, air taxi services, air traffic management services, general aviation (such as training flights, aerial crop dusting, and aerial photography), and airport operations (Gerede, 2006).

Within this sector, various businesses operate, including airlines, air taxi companies, aircraft leasing companies, aircraft maintenance firms, and aviation training and service providers (fuel, ground services, cleaning, and catering). These organizations engage in commercial passenger transport, cargo services, private flight services, and other supportive commercial activities related to aviation. This diversity of services emphasizes the complexity and broad nature of the civil aviation industry (Wittmer et al., 2011b).

2.2. Airline Sector

The airline industry includes commercial activities involving passenger and/or cargo transportation using aircraft. This sector includes domestic and international flights, offering regular or charter flight services through various airline companies and their supporting service providers. Airlines operate to transport people and goods from one location to another quickly and safely for commercial purposes.

The airline sector offers various services, including major international airlines, regional airlines, low-cost carriers, charter airlines, and cargo air transport companies. It provides critical infrastructure for global tourism and business, and functions as a lifeline of the global economy. Airlines' operations are supported by auxiliary services

such as airport management, air traffic control, aircraft maintenance and repair, ground handling services, and aviation security (Hanlon, 2006).

Research revealed that aircraft maintenance planning impacts maintenance costs and airline profitability, and that proactive maintenance planning reduces maintenance costs and increases airline profitability (Aksoy & Okan, 2021).

The airline industry's structure consists of several components that work together. Some of the fundamental elements that constitute the airline industry (Belobaba et al., 2009):

- **Airlines:** This category includes major international carriers, regional, charter, cargo, and low-cost airlines. Each airline company develops different business models to serve specific market segments and customer needs.
- **Airports:** Airports provide the essential infrastructure for the airline sector. They serve as the departure and arrival points for passenger and cargo flights. Airport operations include terminal services, ground services, security, and baggage handling.
- **Air Traffic Control (ATC):** ATC is responsible for managing the airspace to ensure that aircraft travel safely and orderly. This system coordinates flights and is responsible for route planning.
- **Aircraft Manufacturers:** Companies like Boeing, Airbus, and Embraer produce the primary vehicles for the airline industry. These firms are involved in aircraft design, manufacturing, and maintenance services.
- **Service and Maintenance Companies:** Regular maintenance and repair of aircraft are critical for the safe operation of the sector. These services are provided by specialized maintenance companies or the airlines' own technical departments.
- **Passenger Services:** Passenger services include ticket sales, check-in procedures, baggage services, cabin services, and customer support.
- **Cargo Services:** Many airlines also transport cargo in addition to passengers. Cargo transportation is a significant source of revenue for the industry and plays a critical role in facilitating global trade (Wittmer et al., 2011a).

The airline industry is built on a complex network of these components and creates an active ecosystem within the global economy. Each element is vital for the total functioning and efficiency of the sector (Belobaba et al., 2009).

2.2.1. Historical Evolution of the Airline Sector

The history of airline transportation dates back to 1903, with the Wright brothers' first powered flight. This event triggered rapid evolution within aviation. By the 1920s, the first commercial airline companies were established, and by the end of the decade, aircraft had become safer and more comfortable, leading to an increase in passenger numbers (Kane, 2007).

Following World War II, airline transportation underwent significant advancements. The invention of jet engines and their introduction into commercial air transport brought significant advancements, accelerating the growth of the sector. Technologies developed during the war were adapted for civil aviation, leading to the jet age in the 1950s. The introduction of jet-powered aircraft like the Boeing 707 and Douglas DC-8 at the end of the 1950s revolutionized the industry, making intercontinental flights popular and more accessible. This period marked a critical change, transforming air travel into an important component of global transport and commerce (Wensveen, 2016).

During the 1970s and 1980s, particularly in the United States, the airline industry underwent significant deregulation. Until the 1970s, the supply side of the airline sector was tightly controlled by governments worldwide. Decisions about which routes could be flown and the pricing of tickets were largely determined by governmental agencies. However, by the late 1970s, deregulation movements began in the U.S., reducing government control over the industry and increasing competition. This shift in policy stimulated the emergence of low-cost carriers, which made air travel more accessible and led to a substantial increase in passenger numbers. This deregulation fundamentally transformed the airline industry, changing it to a more competitive market and driving innovation and efficiency among carriers (Kole & Lehn, 1999).

The technological advancements at the end of the 20th century and the beginning of the 21st century have enabled the development of larger and more efficient aircraft, such as the Airbus A380 and Boeing 787. These planes have set new industry standards with their increased passenger capacity and fuel efficiency (Bood & Ison, 2017).

However, alongside these developments, the airline industry has faced significant challenges since the 1970s. The oil crisis of the 1970s significantly increased fuel costs for airlines. The 9/11 attacks in 2001 heightened security concerns and led to a temporary downturn in the airline industry. The global financial and economic crises of the 1990s and 2008 placed economic difficulties on the sector. Most recently, the COVID-19 pandemic caused a historic decline in global aviation, forcing many airlines to halt or significantly reduce their operations. These topics will be explored in more detail in subsequent sections of the study, which will highlight how external shocks have continuously impacted the airline industry over the decades (Jang et al., 2011).

During the foundational years of airline transportation in the 1910s and 1920s, passenger numbers were quite limited. Flights were primarily conducted for the purpose of mail transportation and small-scale passenger services. It was also during this era that the first commercial airline companies were established. For instance, KLM was founded in the Netherlands in 1919, Qantas in Australia in 1920, and Delta Air Lines in the United States in 1924 (Wensveen, 2007).

The 1930s marked the introduction of aircraft like the Douglas DC-3, which revolutionized commercial aviation in that era. The DC-3 offered greater passenger and cargo capacity than the aircraft models then in use, making air travel more economical and accessible. During this time, major airlines such as Pan Am, Trans World Airlines (TWA), and British Airways began to serve international routes (Wald et al., 2010).

Following World War II, a new era of development began for airline transportation. Aircraft such as the Lockheed Constellation and the Boeing 707 enabled faster and longer-distance flights. This period also saw the introduction of jet aircraft, which further accelerated international travel. Airlines expanded their global networks, using

jet aircraft, which significantly reduced travel time across the world and increased the global connectivity offered by airlines (Karatay et al., 2014).

In the 1960s, jet aircraft like the Boeing 737, which fundamentally transformed airline transportation, were introduced to the sector. This era initiated a new phase in air travel, significantly increasing passenger numbers and transforming airline transportation into a mass transit system. Airlines could now transport more people faster and more economically than ever before (Karatay et al., 2014).

Deregulation and market liberalization, particularly starting in the late 1970s in the USA, increased competition and led to lower ticket prices, further increasing passenger numbers. Simultaneously, the popularity of wide-body aircraft like the Boeing 747 made international travel more accessible, marking a significant era of growth and accessibility in air travel (Avent-Holt, 2012).

In the 1980s and 1990s, the rise of low-cost carriers (LCCs) changed the aviation sector significantly. With LCCs offering cheap tickets, more customers have been able to access air travel. This period saw a significant increase in passenger numbers as air travel became more affordable. Low-cost carriers like Southwest Airlines, Ryanair, and EasyJet surged in popularity. These airlines democratized air travel by offering affordable travel options, opening up the airline market to broader demographics (Alderighi et al., 2012).

Technological advancements in aircraft design also played a critical role; models like the Airbus A320 and Boeing 777 set new standards in efficiency and passenger comfort, enhancing the overall travel experience and operational efficiency.

In the 20th century, globalization and the increasing travel demands of a growing population led to a significant rise in passenger numbers. Innovative aircraft such as the Airbus A350, A320neo, and Boeing 737MAX provided the capability to cover longer distances more economically with less fuel consumption, making international travel more widespread and affordable. Additionally, the increase in internet access and online ticketing transformed travel planning into a more accessible and flexible experience (Şahin Rodoplu, 2020).

In the 2000s and 2010s, the airline sector expanded even further, driven by globalization and economic growth. Particularly in the Asia-Pacific region, rapid economic development led to a significant increase in passenger numbers (Yao & Yang, 2012).

The COVID-19 pandemic, which began in 2020, caused a huge drop in airline passenger numbers. The industry started recovering gradually in 2021 and 2022, with passenger numbers slowly increasing. Recovery rates varied depending on the region and market type, influenced by factors like vaccination rates, relaxed travel restrictions, and economic conditions (Kökény et al., 2022). Figure 2.1. shows recent evolution of the passenger numbers in the global airline industry, 2023 numbers are showing estimation, 2024 numbers are forecasted.

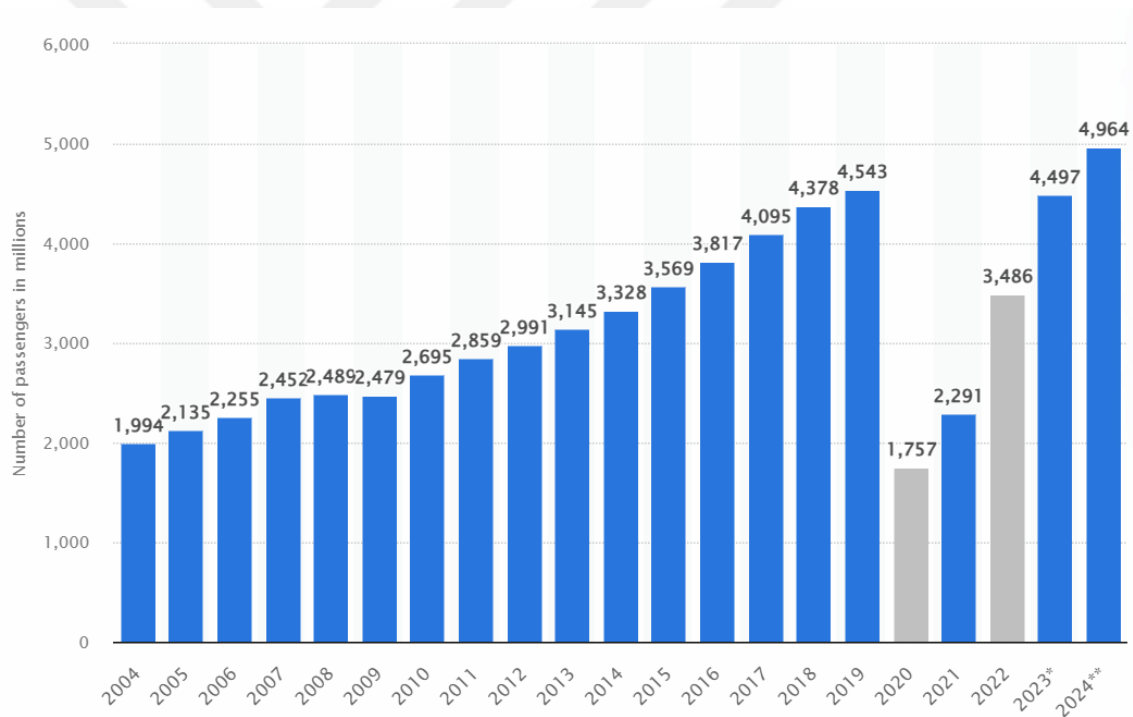


Figure 2.1. Number of Passengers in the Airline Industry 2004-2024 (Millions)

Referece: Statista, 2024

2.2.2. Airline Sector in Türkiye

The development of aviation in Türkiye was shaped during both the late years of the Ottoman Empire and the early years of the Republic. The establishment of the Ottoman

Air Force in 1911 marked the beginning of military aviation in Türkiye. Civil aviation activities started in the 1920s, and significant steps towards civil aviation were taken with the founding of the Turkish Aeronautical Association (later renamed the Turkish Air Association) in 1925 (Bakırcı, 2012).

Before 1933, airline transportation in Türkiye was primarily limited to military purposes. The establishment of the first flight schools in Istanbul during the Ottoman Empire in 1911 played a crucial role in laying the foundations for aviation. After the proclamation of the Republic, some foreign airlines conducted small-scale civil aviation operations in Türkiye. However, systematic development in terms of civil airline transportation began with the establishment of Turkish Airlines in 1933 (Nergiz, 2008).

Significant figures have been noted for the development of aviation in Türkiye. Vecihi Hürkuş (TVHMD, 2008) is known as a pioneering pilot and aircraft engineer in Turkish aviation history, and he is recognized for building Türkiye's first domestic aircraft. In the 1930s, Nuri Demirağ (Yalçın, 2009) established Türkiye's first aircraft factory, leading the way in domestic aircraft production. This period is considered the time when the foundations of Türkiye's aviation infrastructure were laid and the national aviation industry began to take shape.

Turkish Airlines was founded in 1933 with the mission of integrating people, cultures, continents, nations, and cities while providing everyone with new and inspiring travel experiences (Okan & Aksoy, 2022). With the establishment of Turkish Airlines (THY), originally known as State Airlines (DHY), in 1933, airline transportation in Türkiye quickly developed. While passenger numbers were initially low, they began to increase in the 1940s. The 1960s and 1970s saw a rise in domestic passenger demand and the opening of new airports, which expanded the airline network. In the 1970s, THY expanded its international network and added modern jet aircraft to its fleet. The development of airline transportation during this period paralleled changes in Türkiye's economic and social structure (Nergiz, 2022).

Since the 1980s, Turkish civil aviation has undergone significant transformation due to liberalization policies and privatization processes. During this period, alongside

Turkish Airlines (THY), numerous private airline companies were established, increasing competition. The 2000s witnessed rapid growth, and Türkiye's strategic location turned Istanbul into a major hub of air traffic. This expansion was supported by new airport projects and technological innovations in the aviation sector, significantly increasing passenger numbers and flight networks (Nergiz, 2023).

Particularly with the opening of Istanbul Airport, the sector experienced significant growth, establishing Istanbul as a global aviation hub. Türkiye's strategic position, alongside rising tourism demand and economic growth, has assisted the expansion of the aviation sector. Today, the sector shows dynamic growth through modern fleets, extensive flight networks, and increasing passenger volumes (SHGM, 2024). As a result of this growth and faster recovery from COVID-19, Istanbul Airport became the busiest airport in terms of traffic count in Europe in 2024 (Table 2.1).

Table 2.1. The Top Busiest Airports in Europe in 2024

No	Airport	Avg. Daily Dep/Arr Flights	% 2023	% 2019
1	Istanbul	1401	+2%	N/A
2	Amsterdam	1336	+6%	-4%
3	London Heathrow	1302	+4%	-1%
4	Paris Charles de Gaulle	1275	+2%	-8%
5	Frankfurt	1204	+2%	-14%
6	Madrid Barajas	1148	+8%	-2%
7	Barcelona	951	+9%	+1%
8	Munich	887	+8%	-22%
9	Rome Fiumicino	862	+18%	+2%
10	London Gatwick	725	+3%	-7%

Referece: EUROCONTROL, 2025a

2.2.3. Specifications of Airline Product

The fundamental product offered by airlines is passenger air transport services. This service offers the safe, fast, and efficient transportation of individuals and groups from

one location to another. Airlines offer this core service across various classes and fares to meet the different needs and preferences. Some key features of the passenger transportation service provided by airlines (Karatay et al., 2014):

- **Safety and Security:** The safety of passengers and crew, as well as flight security, are top priorities.
- **Speed:** Air transport provides the advantage of covering long distances in short periods.
- **Comfort:** Different comfort levels are available through various class options.
- **Accessibility:** Offers a broad network of destinations across a wide geographic area.
- **Scheduling:** Provides flexible travel opportunities with regular and frequent flights.
- **Additional Services:** Additional services include meals, entertainment, and baggage handling.

Airline transportation service has unique economic characteristics that distinguish it from physical products manufactured in the real sector. One of the primary features is that the service is "non-storable"; if a seat remains unsold after the airplane takes off, it cannot be stored and sold later. This means the economic value of that seat is lost for that particular flight, which leads to a revenue loss (Vasigh et al., 2013).

The non-storability and cost structure of airline services make them distinct from traditional goods, where production can often be scaled to meet demand, and unsold inventory can be stored and sold later. In contrast, every empty seat on a flight represents a lost opportunity that cannot be regained, emphasizing the importance of demand forecasting and pricing strategies in the airline industry (Doganis, 2010).

Airline services also require high fixed costs, including the costs of aircraft, maintenance, and crew salaries, which are significant irrespective of whether the plane flies full or not. However, the marginal costs are relatively low, meaning the cost of carrying one additional passenger is minimal compared to the total cost of operating a

flight. This economic structure necessitates effective capacity and revenue management by airlines to maximize profitability (Stalnaker et al., 2018).

2.2.4. Sector-Specific Properties of the Airline Sector

The airline sector is highly sensitive to demand elasticity and seasonal fluctuations, which necessitates dynamic pricing and revenue management to respond effectively. This characteristic distinguishes airline services economically from physical products in the real sector, which do not usually require such immediate adjustments to pricing based on fluctuating demand (O'Connor, 2001).

Airline companies show industry-specific features such as high fixed costs, intense capital requirements, operational constraints tied to air traffic rights, and compliance with international regulations. Additionally, the airline industry is significantly impacted by environmental factors like weather and economic fluctuations. Airlines are also subject to strict regulatory and security limitations (Holloway, 2008).

Moreover, airline operations are influenced by a large number of external factors, including economic conditions, fluctuations in oil prices, political and legal elements, technological advancements, competitive dynamics, consumer preferences, and global health crises. These factors can directly impact the financial performance, operational strategies, and market positioning of airline companies, which makes the management of airlines a complex and dynamic challenge (Macit, 2021).

2.2.5. Classification of Airline Companies

As competition in the digital age increases significantly, new business models, approaches, and strategies have emerged across every aspect of the business ecosystem to address financial challenges, ensure sustainability, and enhance financial/operational performance and profitability. Businesses that can adapt to and effectively implement new business models have gained an advantage (Hacioglu & Aksoy, 2021).

Airlines vary according to the way transportation services are offered. These models differ in scope of service, cost structure, target market, and revenue generation strategies. From small airlines to large corporate players, each airline defines its position in the market through the type and scope of services it offers. In this section, various airline business models such as full-service, low-cost, regional, charter, and cargo transportation will be examined, focusing on their roles in the aviation sector and their economic characteristics (Zhang, 2018).

2.2.5.1. Full-Service Carriers

Full-service carrier airlines offer a comprehensive range of services, catering to both international and domestic travelers across numerous destinations. These carriers provide services across multiple classes such as economy, business, and first class, ensuring a diverse in-flight experience. Passengers benefit from free meals, baggage services, extensive cabin services, and frequent flyer programs. Full-service airlines emphasize high-quality service and superior customer experience, which generally positions them as a higher-priced option compared to budget carriers. They aim to provide a whole and luxurious travel experience, often including additional amenities like lounge access and priority boarding. This focus on customer satisfaction and extensive route networks supports their position in the competitive airline market, which attracts business and leisure travelers who give importance to comfort and convenience (Ko, 2016).

2.2.5.2. Low-Cost Carriers

Low-Cost Carriers (LCCs) are airlines designed to provide economical and efficient flight options, making air travel more accessible. LCCs reduce operational costs by offering simplified services or a minimal level of service. They typically provide a single-class cabin service and charge passengers for additional services. By operating point-to-point direct flights, LCCs increase operational efficiency, contrasting with the connected routes offered by larger airline networks. This business model allows LCCs to offer lower fares, which is particularly attractive to budget-conscious travelers, and increases competition within the airline industry (Freiberg & Freiberg, 1998).

2.2.5.3. Regional Airlines

Regional airlines operate flights within a specific geographic area, typically connecting small to medium-sized cities to major aviation hubs or other local destinations. These carriers play a crucial niche role by serving markets that larger airlines do not reach. Due to generally lower passenger numbers, regional airlines often use smaller, fuel-efficient aircraft to operate their routes efficiently. This focus allows them to provide vital connectivity and enhance accessibility to air travel in less populated regions, supporting local economies and offering travel options that might otherwise be unavailable (Oktal & Küçükönel, 2007).

2.2.5.4. Charter Airlines

Charter airlines offer specialized flight services to specific customer groups, typically operating flights that are leased for a certain period by organizations such as tour operators, corporations, or sports teams. These airlines often arrange flights as part of holiday packages to tourist destinations, special events, or business trips. The charter model provides flexible flight schedules and usually offers more cost-effective options compared to regular airlines, making it particularly suitable for groups seeking private or customized travel solutions. This flexibility allows charter airlines to meet the specific travel needs of their clients, whether for leisure, corporate, or other specialized travel purposes (Doganis, 2005).

2.2.5.5. Cargo Airlines

Cargo airlines focus especially on the transportation of freight and cargo, providing essential services for urgent shipments, mail transport, and specialized cargo needs. These carriers typically use large-capacity and specially equipped aircraft to facilitate global trade, playing a vital role in the logistics chain. The rise of e-commerce has driven significant growth in this sector, as cargo airlines are crucial for the rapid and efficient delivery of goods across vast distances. They ensure that businesses can meet demand fluctuations quickly, contributing to the overall efficiency and reaction of the global market (Aksoy & Baş, 2021).

CHAPTER III

PERFORMANCE INDICATORS OF AIRLINE COMPANIES

In the airline industry, performance indicators play a crucial role in measuring the operational and financial success of companies. This section will explore commonly used performance indicators within the sector, explaining how they are calculated, their significance, and their roles within the dynamics of the industry.

Performance analysis in airlines covers a wide spectrum from financial status to service quality, operational efficiency, and customer satisfaction. Moreover, for publicly traded companies, there are specific indicators used to measure stock market performance. Since these indicators are also part of the research question for this study, this section will provide information about airlines' financial measures regarding stock exchanges.

3.1. Performance Measurement in Companies

Performance in companies incorporates several dimensions, including financial health, operational effectiveness, and market positioning. Performance measurement is used to gauge whether a company has achieved its goals and maintained its competitiveness in the market. Financial indicators, operational metrics, market share, customer loyalty, and the capacity for innovation are all examined to assess a company's overall success. Effective performance management supports strategic decision-making processes and continuous improvement (Coşkun, 2006).

3.2. Performance Indicators of Airline Companies

Performance indicators in airline companies are critical tools for evaluating a company's operational and financial status. These metrics effectively measure the

market position, efficiency, and quality of customer service of an airline (Yaghi, 2015):

- **Financial Performance Indicators:** These are used to assess a company's economic situation and profitability. Key financial metrics include revenue, profit margins, operational costs, return on investment (ROI), and debt ratios. These indicators form the foundation for analyzing the financial health, market position, and value to investors of a company.
- **Operational Performance Indicators:** These are crucial for evaluating the operational efficiency of an airline. Common operational metrics might include load factor, on-time performance, passenger numbers, and flight numbers. These indicators help management to optimize operations and improve service delivery.
- **Market-Related Performance Indicators:** In the context of publicly traded companies, certain indicators like stock performance, market capitalization, and earnings per share are monitored closely. These reflect the company's position in the financial market and can influence investor decisions (Duc Thinh & Ngoc Lam, 2020).

While the literature is focused mainly on studies analyzing financial indicators, this study will focus on operational indicators. This approach allows for a deeper understanding of how well the company is performing operationally and its implications in the market. This will offer a more rounded view of its overall health and future opportunities.

3.3. Financial Indicators of Company Stocks

Stock exchanges are regulated markets where securities are bought and sold. Stocks, bonds, and other financial instruments issued by companies, governments, and other entities are traded on these markets (Ratanapakorn & Sharma, 2007).

Companies typically go public on the stock exchange to raise capital from a broader number of investors, enhance corporate value, and expand their operations. Rather than increasing financial liabilities through borrowing new debt, firms needing more

financial resources choose to partially go public. By selling shares to the public, they generate revenue, which can then be invested back into their projects. Through initial public offerings (IPOs), they can gather funds from a larger number of investors. Being listed on the stock exchange provides companies with prestige among investors, enhancing the liquidity of their shares, meaning that the stocks can be bought and sold more easily and quickly. It also offers founders and early investors the opportunity to exit their investments and realize profits. Going public presents significant opportunities and challenges for a company and is a critical component of its future growth and success (Gençtürk, 2009).

One of the fundamental benefits of investing in the stock market is capital appreciation. As companies grow and their profitability increases, the value of their stocks typically rises. This offers investors the opportunity to enhance the value of their investments through an increase in capital value over time. The primary reasons for purchasing stocks are the expectation of capital gains from corporate investments and receiving dividends. Stocks provide investors with the chance to benefit from the growth potential of companies and protect their portfolios against economic fluctuations. Investing in the stock market also offers investors the opportunity to gain in-depth knowledge about financial markets, economics, and business management. During this process, investors develop skills such as analytical thinking, risk assessment, and strategic planning. Stock exchanges promote economic growth and development while ensuring the liquidity and functionality of capital markets (Karslı, 1994).

Measuring company performance enables investors to make informed decisions about the firms and enhances market efficiency. The relationship between company performance and stock prices is one of the fundamental dynamics of financial markets. Investors seek information about companies' financial statuses, revenues, profitability, growth potential, and risk profiles. This information plays a critical role in decisions to invest in, continue holding, or sell stocks. Measuring company performance promotes competition within and across sectors. Companies seek ways to enhance their operational and financial efficiencies by comparing their performance with competitors (Horasan, 2008).

Financial indicators related to the stock market are utilized to assess companies' market value, investor confidence, and economic health. Metrics such as stock prices, the market value-to-book value ratio, and the price-to-earnings ratio reflect a company's performance, its position in the industry, and its potential for future growth. These indicators are critically important for investors and managers in understanding a company's financial situation and making strategic decisions (Çevik, 2016).

3.3.1. Stock Price

Stocks represent ownership units of a company and determine the shareholders' stakes in the company. Stocks grant rights to a share of the company's profits and a voice in its management. Traded on stock exchanges, stocks serve as a means for investors to achieve capital gains and generate income. They are one of the primary methods for companies to raise capital (Karabıyık, 1997).

Stock prices are determined by supply and demand dynamics. Factors such as a company's financial health, its position within the industry, economic conditions, and overall market trends influence investors' demand for a stock and thereby its price. Investors' perceptions of the company, financial performance reports, and market news can directly impact prices. Stock prices are continuously updated through market transactions and fluctuate based on the trading decisions of investors (Yaman, 2016).

Stock prices reflect a company's market value and the performance perceived by investors. Factors like the company's financial condition, future earnings potential, and market conditions affect stock prices. Investors and analysts use changes in stock prices to gain insights into the health of the company and industry trends. Generally, rising stock prices of high-performing companies are seen as indicators of success (Cengiz & Püskül, 2016).

3.3.2. Earnings Per Share

Earnings Per Share (EPS) represents the amount of a company's net profit allocated to each share of stock. It is calculated by dividing the company's total net profit by the number of shares in circulation. This ratio is used to measure a company's profitability

and the economic value of each share, providing investors with a crucial indicator of the company's financial health and performance (Welch, 2004).

EPS assists investors in understanding the profitability of a company and the yield of a stock. Companies with a high EPS are generally considered more profitable. Investors and analysts track changes in EPS over time to assess trends in a company's financial performance and conduct comparative analyses. Earnings Per Share is a vital financial metric that guides investment decisions (Chen, 1986).

3.3.3. Price/Earnings (P/E) Ratio

The Price/Earnings (P/E) ratio indicates the proportion of a company's stock price to its earnings per share. This ratio is used to determine how the stock price compares to the company's earnings. To calculate it, the market stock price of the company is divided by the net earnings per share (EPS). A high P/E ratio may suggest that the shares are relatively expensive in the market, while a low P/E ratio may indicate that the shares are comparatively cheap. This ratio is utilized by investors to assess a company's valuation and potential growth expectations (Fama & French, 1992).

The Price/Earnings (P/E) ratio shows how much a company's stock price is valued against its earnings and is used to assess whether the market value of the company is fair. Investors use this ratio to analyze a company's financial health, its position in the market, and its future growth potential. If the P/E ratio is high, the stock might be considered overvalued; if low, the stock might be undervalued. Therefore, it plays a crucial role in investment decisions (Martikainen, 1989).

3.3.4. Market Value to Book Value (P/B) Ratio

The Market Value to Book Value (P/B) ratio indicates the ratio of a company's stock market value to its book value. The market value is determined by multiplying the market price of the stock by the total number of shares in circulation. The book value is calculated by subtracting the company's liabilities from the total assets registered in the financial statements. The P/B ratio is used to analyze how a company's shares are valued in the market compared to their book value (Fama et al., 1969).

The Market Value to Book Value (P/B) ratio illustrates how much a company is valued in the market compared to its accounting value. If the company's market value is high, it may indicate that investors view the company as having more potential for future growth. A low P/B ratio suggests that the company is traded at a lower value in the market relative to its accounting value, potentially indicating it is undervalued. This ratio is used by investors to assess companies' performance and growth potential (Brahmasrene & Jiranyakul, 2007).

3.4. Operational Performance Indicators of Airline Companies

In companies, operational performance indicators measure the efficiency of operations using non-financial metrics. Operational performance is assessed in areas such as market response time, product or service quality, customer service effectiveness, and the optimization of internal processes. These indicators are critically important for improving business processes and achieving strategic goals.

The importance of using operational performance indicators in airline operations comes from their ability to accurately measure and evaluate the efficiency of business processes, adaptability to market dynamics, quality of service, and customer satisfaction. These indicators assist in monitoring a company's operational effectiveness, identifying issues, and determining opportunities for continuous improvement. Effective operational performance management plays a crucial role in making strategic decisions aimed at reducing costs, enhancing service standards, and gaining a competitive edge (Schefczyk, 1993).

3.4.1. Available Seat Kilometers

As previously mentioned, the concept of production in airline companies is significantly different from the physical product concept in real sector companies. Initially, airline companies offer their potential customers, the passengers, a seat for use as their product. Accordingly, to measure production capacity or quantity, airline companies need to assess the offered seat capacity on specific flights or routes during a certain period (Yaşar & Gerede, 2023).

Considering the characteristics of the airline product, it becomes apparent that measuring the offered seat count alone is insufficient for assessing the production quantity of airline companies. This is because different airlines operate the seats they offer over varying distances. For example, airlines such as Singapore Airlines, Emirates, and Qatar Airways operate from countries that are relatively small in size. Due to this small size, these countries do not have domestic flights. Consequently, these airlines are required to offer their services over longer international distances, necessitating a different approach to measuring their production output (

Figure 3.).



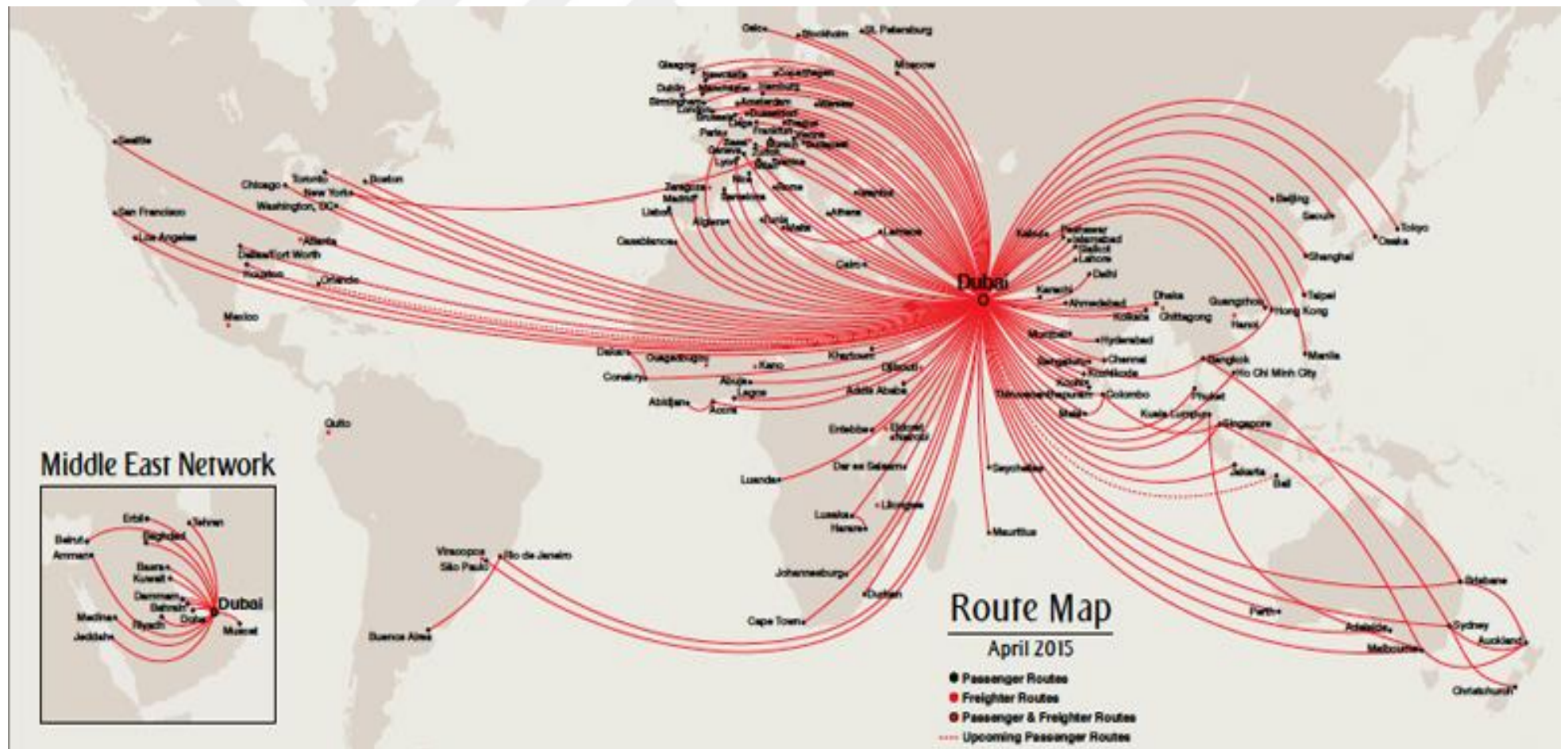


Figure 3.1. Emirates Route Map
 Referece: Business Traveller, 2015

On the other hand, airlines like Widerøe, a regional airline serving small airports in the northern cities of Sweden, typically provide more frequent flight services over shorter distances. Consequently, the production quantity for airlines like Widerøe would differ from those mentioned in the previous paragraph that operate longer international routes (Figure 3.).



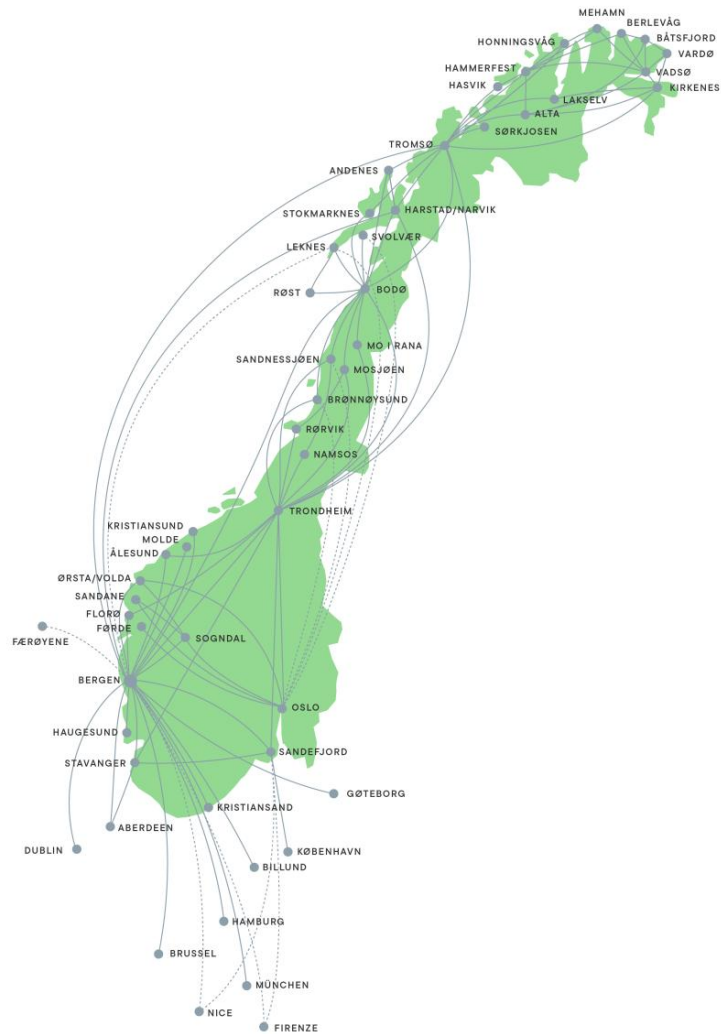


Figure 3.2. Wideroe Route Map
 Referece: Wideroe, 2024

Additionally, there are airlines that serve a mix of both scenarios. These airlines operate in countries with sufficiently large geographical areas to offer relatively short domestic flights, while also flying long international distances. These operations are conducted concurrently. In the scope of this study, airlines such as Turkish Airlines (THY), Lufthansa, and American Airlines have been selected to compare their operations across different geographic regions, providing a comprehensive view of how diverse airline models manage their service offerings.

Due to the reasons discussed, measuring an airline's production accurately requires assessing not only the seat supply but also the distance that each offered seat travels on a specific flight. This approach fully captures the production output of an airline.

Based on this information, the production capacity of airline companies is measured by ASK, or Available Seat Kilometers. ASK represents the total seat kilometers capacity of an airline, calculated by multiplying the number of seats offered on a flight by the distance of the flight. This metric indicates the maximum passenger carrying capacity an airline can offer on a specific flight, providing insights into the airline's size and operational capacity (Schefczyk, 1993).

The importance of using ASK lies in its ability to measure an airline's capacity utilization and market expansion potential. This metric indicates how efficiently an airline operates and how well its carrying capacity aligns with market demand. High ASK values imply a broad operational network and a high capacity offering, which can enhance an airline's growth and revenue potential (Tsikrikitis, 2007).

Airlines that identify opportunities in the market and wish to address these gaps may need to increase their ASK by adding more flights, expanding their routes, and possibly deploying larger aircraft to serve these new demands. This strategic increase in ASK allows airlines to better meet market needs and capitalize on potential growth areas, enhancing their competitive edge in the industry.

3.4.2. Revenue Seat Kilometers

Similar to ASK, the RPK (Revenue Passenger Kilometers) value is used to measure how many of the offered seats are utilized by fare-paying ticketed passengers. RPK is calculated by multiplying the number of passengers an airline carries by the kilometers it flies. This metric indicates the volume of passenger transportation that an airline achieves and its revenue potential. RPK is utilized by airlines to assess passenger demand and market penetration (Yaşar & Gerede, 2023).

RPK measures an airline's passenger transport performance and whether its response to market demand is adequate. It counts the number of transported passengers and the

flight distances to show the total passenger transportation volume of the airline. This indicator is a fundamental tool in evaluating operational efficiency, market share, and revenue generation capacity (Macit, 2021).

The RPK value indicates how much of the product offered is being consumed by customers, i.e., passengers. Airlines aiming to increase their revenue from the product offered should attempt to enhance their RPK value.

3.4.3. Load Factor

The Load Factor is calculated by comparing the two operational values mentioned earlier. It is an indicator that shows how much of an airline's seat capacity is utilized. Expressed as a percentage, the load factor is calculated by dividing the number of passengers carried in revenue passenger kilometers (RPK) by the total available seat kilometers (ASK). A high Load Factor indicates that the airline is using its capacity effectively by carrying more passengers, which is a crucial factor demonstrating operational efficiency and revenue optimization (Stalnaker et al., 2018).

The use of the Load Factor is vital for measuring the efficiency of capacity utilization in airline companies. A high Load Factor indicates that a significant portion of seats on flights are filled, which is generally associated with higher revenue and operational efficiency. This metric plays a critical role in capacity planning, pricing strategies, and assessing overall business performance (Zuidberg, 2014).

However, there is a sensitive point when measuring the Load Factor. If an airline keeps ticket prices very low, it might achieve a high RPK and maintain a high load factor by selling all the seats offered, but it may not reach the level of revenue necessary to turn a profit. This scenario raises the issue of how many seats are sold at what price and how to maximize revenue, which is a subject of Revenue Management. While there is extensive literature on this topic, it is beyond the scope of this study and will not be covered here (Swan, 2002).

3.4.4. On-Time Performance

On-time performance is an indicator that shows how closely an airline's flights adhere to their scheduled departure and arrival times. It is usually calculated as the percentage of flights that depart or arrive within a specific timeframe from the scheduled time (e.g., within 15 minutes). This ratio provides significant insight into an airline's operational efficiency and reliability (OAG, 2016).

The use of on-time performance is critical in evaluating an airline's ability to provide timely service. This directly affects customer satisfaction and operational efficiency. Airlines with high on-time flight performance gain an advantage in reliability and customer preference, which strengthens brand image and customer loyalty in a competitive market. This performance metric is essential for maintaining a positive reputation and can significantly influence passengers' choice of airlines, ultimately impacting the airline's profitability (Khim et al., 2010).

3.4.5. Utilization of Aircraft

The utilization rate of aircraft indicates how effectively an airline uses its fleet. It is typically calculated based on the number of flying hours per aircraft on a daily or yearly basis. This metric measures how much time aircraft spend in the air compared to the time they are on maintenance or standby, thus showing how efficiently an airline utilizes its assets (Barbot et al., 2008).

The use of the aircraft utilization rate is crucial for evaluating the fleet efficiency of airline companies. This indicator shows how long the aircraft are operational and, consequently, the efficiency of the company's asset utilization. High utilization rates suggest that an airline is using its aircraft in the most efficient way possible, optimizing operational costs. This is a critical operational efficiency metric that has a direct impact on financial performance, helping airlines maximize revenue from their available fleet and reduce unit costs through better asset management (Tanebe & Fukumoto, 2011).

3.5. Relationship between Operational Performance Indicators and Financial Performance Indicators of Airline Companies

Operational performance indicators in the airline industry, such as load factor, on-time performance, Available Seat Kilometers (ASK), and Revenue Passenger Kilometers (RPK), are crucial for evaluating both the day-to-day and strategic efficiency of airlines. These metrics reflect how effectively an airline is utilizing its resources and maintaining operational efficiency to generate revenue. Meanwhile, stock market-related financial indicators, such as earnings per share (EPS), price-to-earnings (P/E) ratios, and market capitalization, mirror the market's perception of an airline's market value and its future profitability. Understanding the relationship between these operational and financial metrics can provide a detailed view into how internal performance impacts external financial perceptions and investor behaviors (Alici, 2020b).

The Load Factor, On-Time Performance, RPK, and ASK are crucial operational metrics in the airline industry that have direct implications for profitability and stock performance. Each of these metrics provides insights into different aspects of an airline's operational efficiency, which in turn influence investor perception and stock prices.

Financial indicators such as stock prices, the Price/Earnings (P/E) ratio, Earnings Per Share (EPS), and market value are crucial tools for investors to assess the value and financial health of an airline. These financial metrics are significantly influenced by the airline's operational performance, which can either support or reduce investor confidence and impact the airline's stock performance and valuation (Kathiravan et al., 2019).

The influence of operational performance on financial indicators (Keles & Ozulucan, 2020):

- **P/E Ratio:** The P/E ratio reflects investor expectations based on the company's current earnings relative to its share price. When operational metrics like load factor, on-time performance, RPK, and ASK indicate high efficiency and

profitability, investor interest and demand for the airline's shares increase. This positive investor sentiment can increase stock prices, raising the P/E ratio. A low P/E ratio in a well-performing company might attract investors looking for undervalued stocks with potential for growth while assuming the operational metrics indicate a strong company profile.

- **Earnings Per Share (EPS):** EPS directly measures the profitability attributed to each share of common stock, serving as a key indicator of financial health. When operational successes, such as increased load factors and efficient fuel management, increase profitability, EPS usually rises. An increase in EPS makes the stock more attractive to investors because it signals that the company is generating more earnings from its operations. Enhanced EPS can lead to a higher stock price as the market values the airline's increased profitability.
- **Stock Price and Market Value:** The market value of an airline is influenced by both its operational and financial performance. Effective operational management that leads to improved profitability and growth potential can significantly increase the airline's market value. Investors often look at operational metrics as predictors of future financial performance and stability. A strong operational performance indicates good management and effective use of assets, which are critical for long-term financial success and can lead to a higher market valuation. Since market value is calculated by multiplying the number of shares by the share price, an increase in market value also indicates an increase in stock price (Keles & Ozulucan, 2020).

For airline management, understanding the relationship between operational performance and financial indicators is crucial for strategic decision-making. Efficient operational management not only improves day-to-day airline functionality but also enhances financial metrics, making the airline more attractive to investors.

For investors, evaluating an airline involves a detailed analysis of both operational metrics and financial indicators. This dual approach allows investors to gain a detailed view of the airline's operational efficiency, financial health, and potential for future growth (Alıcı, 2020a).

The relationship between operational and financial metrics in the airline industry underscores the importance of efficient operations as a foundation for financial success. Airlines that master this balance tend to receive stronger investor confidence, better market valuation, and a competitive edge in the industry.

For these reasons, monitoring and improving operational indicators are crucial for improving the financial success of airline companies. Some areas where this plays a significant role includes (Tsikrikitis, 2007):

- **Cost Management:** Operational efficiency directly influences cost management. For example, optimizing fuel consumption, reducing turnaround times, and improving maintenance scheduling can significantly decrease operational costs. Lower costs can turn into higher profits, positively affecting the company's bottom line and attractiveness to investors.
- **Revenue Maximization:** Operational indicators like load factor and RPK indicate how effectively an airline is generating revenue from its available resources. High performance in these areas suggests that the airline is not only filling its seats but also maximizing the revenue from each flight. This efficiency attracts more investments as it reflects the company's ability to capitalize on its assets well.
- **Investor Confidence and Market Perception:** Investors closely watch operational metrics as they can provide early signs of issues that might affect profitability. They can also indicate signals of effective management that could lead to better-than-expected financial results. An airline that shows consistent improvement in operational metrics is often viewed as a safer and potentially more profitable investment (Karan, 2004).
- **Strategic Decision Making:** Operational performance data helps airline management in making informed strategic decisions, such as route planning, fleet expansion, and service improvements. These decisions directly affect financial performance by influencing both costs and revenues.
- **Competitive Advantage:** In a highly competitive industry, airlines with superior operational efficiency can offer more competitive pricing, better reliability, and higher service quality, all of which contribute to stronger brand

loyalty and customer retention. This competitive edge can lead to better financial performance as reflected in stock prices and market share.

In summary, the close relationship between operational performance and financial metrics underscores the need for airline companies to maintain focus on enhancing operational efficiency. This not only improves the financial health of the airline but also strengthens its position in the stock market, increasing shareholder value over the long term.



CHAPTER IV

EFFECT OF GLOBAL EXTERNAL SHOCKS ON AIRLINE COMPANIES' PERFORMANCE AND COVID-19

Global external shocks have a significant impact on the airline industry, which is highly sensitive to economic, political, and environmental changes. These shocks can range from oil price fluctuations, economic recessions, security threats, to health crises like pandemics, which are affecting demand for travel, operational costs, and the overall economic stability of the airline sector. This chapter will look in detail at how these various external shocks impact the airline industry. Also, how companies typically respond and adapt to these external shocks will be discussed as well.

4.1. Global External Shocks

An external shock is an economic, environmental, or political change that derives from events beyond a business's control, mainly unexpected. Such shocks can directly or indirectly affect the operational and financial performance of businesses. For companies, external shocks often affect various areas such as market dynamics, supply chains, raw material prices, exchange rates, and interest rates (Malik & Hammoudeh, 2007).

External shocks are generally unforeseeable and uncontrollable factors for businesses, but being resilient to these shocks is critical for the long-term success of the company. Companies must implement methods such as risk management strategies, diversification, flexible operational structures, and rapid adaptation capabilities to develop resilience against such shocks (Malik & Hammoudeh, 2007).

Global external shocks can be defined as the worldwide impact of the external shocks mentioned above, affecting an entire sector or area globally. The aviation industry, by its nature as a global connector of the world, is among the sectors most affected by global external shocks.

External shocks impacting the airline industry consist of economic, environmental, and social events. Economic crises can lead to a decrease in general demand and passenger numbers, thus reducing company revenues. Changes in oil prices directly affect operational costs by increasing jet fuel prices. Geopolitical tensions and wars can disrupt flight paths and security, leading to the closure or rerouting of flight routes. Natural disasters can damage infrastructure and interrupt operations. Health crises, especially the COVID-19 pandemic, have significantly reduced travel demand and accelerated structural transformations in the airline industry. These shocks test the financial stability, market strategies, and operational resilience of airline companies, forcing continual adaptation and innovation (Mantin & Wang, 2012).

The aviation sector is particularly sensitive to the impacts of external shocks for the following reasons (Jang et al., 2011):

- **High Fixed and Variable Costs:** The aviation industry operates with high fixed and variable costs (such as aircraft purchase, maintenance, fuel, and personnel expenses). Therefore, any external shock that affects costs can significantly impact profit margins. For example, a sudden increase in oil prices can drastically raise fuel expenses, directly affecting the industry's overall cost structure and reducing profitability.
- **Demand Elasticity:** Demand for aviation services is closely tied to general economic conditions and consumer confidence. During economic downturns, people often tend to reduce their travel expenses, which can lead to a rapid decline in demand for the aviation sector. This sensitivity makes the industry vulnerable during financial crises when discretionary spending is reduced (Jang et al., 2011).
- **Global Connections:** The aviation sector is linked to international trade and travel, which makes it directly sensitive to global economic and political events. A crisis in one region can quickly spread and affect operations globally.

For instance, the Russia-Ukraine conflict affected Finnair's flight routes to the east. Due to the conflict, Finnair could not fly over Russia and had to shift its route to the south over Türkiye, extending its flight paths and exceeding the maximum range of its aircraft, eventually leading to the closure of some routes (Sopamena, 2022).

- **Strict Regulations:** The aviation industry is subject to strict regulations concerning safety and environmental standards. Changes in these regulations can have effects on the sector. For example, new safety regulations might require costly updates to equipment or changes in operational procedures and environmental regulations, which could introduce additional costs for carbon emissions limitations.

Understanding these vulnerabilities is crucial for the industry to prepare and adapt to potential challenges. Strategies such as diversifying income streams, enhancing flexibility in operational procedures, and maintaining strong liquid positions can help airlines manage the impacts of external shocks more effectively. Additionally, continuous risk assessment and the implementation of robust crisis management procedures are essential for sustaining operations during turbulent times.

Over the course of its history, the aviation sector has been significantly affected by external shocks that have deeply influenced its operational and financial performance. These shocks vary from economic crises and technological advancements to health crises and geopolitical events. Some of the most impactful external shocks are the following (Wang, 2013):

- **Economic Recessions and Crises:** Financial crises or periods of economic downturn can reduce consumer demand and investments, which leads to declines in business revenues. Global or regional economic crises can weaken people's ability and willingness to travel, which results in decreased demand and lower revenues. Even a regional crisis can easily impact the global structure of the aviation sector due to its interconnected nature. For instance, the global financial crisis of 2008 triggered a worldwide economic slowdown and severely affected the aviation sector. There were significant declines in both business and leisure travel, and many airline companies either went

bankrupt or sought financial assistance. The regional financial and economic crises of the 1990s, while financially impacting a specific region, reduced travel demand within that region, thereby creating a global effect on the aviation sector (Mollick & Assefa, 2013).

- **Political and Geopolitical Developments:** Political events such as new government policies, trade wars, tax regulations, or legislative changes can affect businesses' cost structures and access to markets. Wars, terrorist attacks, political instability, and diplomatic crises can reduce travel demand to certain regions and lead to operational disruptions. For example, one country may be in a political crisis, and another country may ban flights to that country. Since the ongoing Russia-Ukraine crisis began in 2022, many countries around the world have banned flights to Russia (Figure 4.). As of 2024, the number of countries not flying to Russia exceeds those that do. As a solid example, no airline based in Europe currently flies to Russia. This situation has significantly affected European airlines both operationally and financially. Additionally, the Cold War era, World War II, and other geopolitical conflicts have been significant external shocks that shaped the aviation sector. During these periods, military aviation saw significant advancements, and the impacts on civil aviation were felt over the long term. Similarly, the Arab Spring movements in the 2010s led to regional instability and a decrease in airline demand (Ennen & Wozny, 2024).



Figure 4.1. British Airways Route Change After Russian Airspace Closure

Referece: Business Insider, 2023

- **Natural Disasters:** Events such as earthquakes, hurricanes, and floods can damage businesses' physical assets, disrupt supply and distribution chains, and lead to operational interruptions. For example, in 2010, the eruption of the Eyjafjallajökull volcano in Iceland temporarily suspended air traffic across Europe. Such disasters can require costly repairs and lead to significant revenue losses due to operational downtime (Plu et al., 2021).
- **Technological Developments and Innovations:** Unexpected technological innovations or changes can create competitive disadvantages for companies that are slow to adapt to those innovations. Rapid technological changes can alter operational practices and competitive conditions in the aviation sector. These shifts can create opportunities for some companies, but on the other hand, present challenges for others. For instance, the development of jet engines and other innovations in aircraft technology has led to significant transformations in the aviation industry. These technological advances assisted the expansion of the industry and made it possible to reach farther destinations in shorter times, thus enhancing connectivity and efficiency. Companies that failed to adapt to these changes fell behind in the competition (Clark, 2018).

- **Sudden Changes in Raw Material Prices:** Fluctuations in the prices of raw materials like oil and metals can impact production costs and reduce profit margins. For the aviation sector, fuel costs constitute a significant portion of total operational expenses. Sudden increases or decreases in oil prices can directly affect the profitability of airline companies. Fluctuations in oil prices, especially during the 1973 oil crisis and the price spikes in the early 2000s, have impacted the aviation sector (Kathiravan et al., 2019).
- **Fluctuations in Exchange Rates:** Sudden changes in exchange rates can affect costs and price competitiveness, especially for businesses heavily involved in international trade. As aviation sector companies operate globally, they often have to deal with currencies other than their own country's currency. Fluctuations in exchange rates used to convert these currencies can reflect as financial costs to airline companies. This impact can complicate budgeting and financial planning, as well as influence the pricing strategies for the various markets in which airlines operate.
- **Regulatory Changes:** Changes in regulations related to aviation safety, environment, and airspace management can significantly impact the operations and cost structures of airline companies. An obvious example in the near future will be the effort to reduce carbon emissions, emphasized by the adoption of Sustainable Aviation Fuel (SAF). Another example is the night flight bans at certain airports. These bans are implemented to reduce aircraft noise around airport vicinities, which can operationally restrict airline companies. Such regulatory changes require airlines to adapt their operational strategies, which may lead to increased costs. For instance, the integration of SAF into fuel supplies not only involves higher costs compared to conventional jet fuel but also may require modifications to infrastructure and supply chains. Night flight bans, while reducing noise pollution, force airlines to restrict flight schedules, potentially leading to decreased utilization of aircraft and reduced revenue in affected routes. Airlines need to stay agile and proactive in their regulatory strategy and plan to minimize disruptions. Compliance with these regulations is crucial not only for maintaining operations but also for building a positive public image and ensuring sustainability in the long-term lifetime of the airline (Ulaştırma Bakanlığı, 2009).

- **The End of the Cold War:** The end of the Cold War significantly influenced the airline industry. After this period, new airspaces opened globally, and airlines were able to enter into new markets that were previously inaccessible. These changes offered airline companies new opportunities to open new routes and expand their flight networks between international destinations. Eastern Europe, Central Asia, and many other regions emerged as new markets for commercial airline companies. Increased flights to these areas significantly boosted global air traffic, contributing to the popularization of air travel. Furthermore, these new markets opened new doors for global tourism and the business sector. This process also accelerated trends in industry such as consolidation, increased international competition, and strategic alliances. The end of this era significantly drove the globalization of the airline industry and laid the foundation for its dynamic structure today (Avent-Holt, 2012).
- **Terrorist Attacks:** Acts of terrorism, such as aircraft hijackings and airport attacks, can temporarily weaken confidence in aviation and lead to a decline in passenger demand. For instance, the terrorist attacks on September 11, 2001, left deep and long-lasting effects on the aviation industry. Following these events, air travel security measures were dramatically increased, leading to additional security costs for airlines. Moreover, these events caused permanent changes in traveler behavior, and many airlines faced financial difficulties (Jang et al., 2011).
- **Health Crises and Pandemics:** Global and regional health crises like the COVID-19 pandemic and SARS have led to significant changes in consumer behavior, disruptions in business operations, and widespread economic impacts. Health crises have severely affected the aviation sector due to travel restrictions and quarantine measures. These situations dramatically reduced aviation demand on both international and regional levels, leading to financial crises across the industry (Carter et al., 2022).

These examples illustrate just a few of the many possible external shocks. However, this discussion is limited to those major external shocks that have a global impact on the aviation sector. Such events underscore the importance of robust crisis management and adaptability in the aviation industry. It also shows the need for

airlines to continually evaluate and enhance their resilience to mitigate the impacts of future shocks.

4.1.1. 1970s Petrol Crisis

In 1973, the Yom Kippur War broke out between Arab countries and Israel. During the war, oil-producing Arab countries initiated an oil embargo against Western countries supporting Israel, which marked the beginning of the 1970s Oil Crisis. In this crisis, Arab oil producers cut oil supply, leading to a sharp decrease in global oil availability and a significant increase in prices. The crisis caused economic slowdowns worldwide, rising inflation, and widespread economic uncertainty. It also triggered a reevaluation of energy policies and increased interest in alternative energy sources (Kathiravan et al., 2019).

The 1970s oil crisis had a profound impact on the aviation industry. The dramatic increase in fuel costs significantly raised operational expenses for airlines, which eventually led to higher ticket prices and reduced passenger demand. The crisis forced airline companies to invest in more fuel-efficient aircraft and to enhance operational efficiency. This period marked the beginning of the aviation industry's focus on cost management and operational efficiency (Kathiravan et al., 2019).

4.1.2. 1997 Asia Financial Crisis

The 1997 Asian financial crisis began in Southeast Asia and quickly spread, crushing the region's financial systems via speculative attacks and causing a collapse in investor confidence. The crisis emerged from unsustainable fixed exchange rate regimes, excessive borrowing, and investment bubbles. The sudden withdrawal of foreign capital led to sharp declines in exchange rates and stock markets (Lee & Hooy, 2012).

The global impact of the Asian financial crisis included slowed growth rates in the world economy and increased instability in global financial markets. The crisis also induced a reevaluation of international financial regulations and oversight (Zhang, 2018).

In the aviation sector, the 1997 Asian financial crisis led to a decrease in demand and revenue losses. The economic downturn in the region adversely affected business and tourism travel. With falling income levels, passengers reduced their demand for airline travel. Airlines faced financial difficulties and a decrease in passenger numbers, which led some of them to declare bankruptcy or undergo restructuring. Additionally, the crisis caused a reassessment of investments and expansion plans within the aviation industry. It also forced companies to reconsider and often limit their growth strategies in response to the new economic conditions (Jackson, 2017).

4.1.3. 2001 9/11

The terrorist attacks of September 11, 2001, in the United States involved the hijacking of four passenger planes, two of which struck the World Trade Center in New York City, one hit the Pentagon, and another crashed in Pennsylvania. These attacks were planned and coordinated by al-Qaeda and had a deep impact globally.

The September 11 attacks significantly affected international relations, security policies, the aviation industry, and the global economy. These events particularly led to increased aviation security measures. Demand for air travel sharply declined, and many airlines faced financial difficulties. The increased operational costs for enhanced security measures, along with decreased passenger confidence, significantly altered how airlines operated, which led to increased ticket prices and the implementation of stricter security checks at airports (Lyon, 2006).

4.1.4. 2003 SARS

The 2003 SARS crisis began as Severe Acute Respiratory Syndrome (SARS) became a global pandemic, originating in Asia and rapidly spreading worldwide. SARS was a contagious disease that was capable of human-to-human transmission and could cause severe respiratory problems.

The crisis was worsened by infected individuals traveling by air, quickly becoming an international health issue. Governments and health organizations implemented quarantine measures and travel restrictions to overcome the spread of the virus. SARS

significantly impacted global travel and trade, leading to serious economic losses in the aviation and tourism sectors (Dombey, 2004).

4.1.5. 2008 Global Financial Crisis

The 2008 financial crisis began with the collapse of the housing bubble in the United States and turned into a global economic downturn. The crisis deepened due to the failure of high-risk mortgage loans, the bankruptcy of financial institutions, and the suspension of credit markets. This led to a halt in global economic growth, increased unemployment rates, and the bankruptcy of many companies. The financial crisis triggered a long-term recession in the global economy and a reshaping of financial regulations (Mollick & Assefa, 2013).

The aviation sector was severely impacted by the 2008 financial crisis. Due to the economic downturn, there was a significant decline in demand for both business and leisure travel. This decrease in travel demand led to reduced revenues for airlines, resulting in bankruptcies or financial restructuring for some of them. Additionally, the tightening of credit made it difficult for airlines to finance expansion and fleet renewal plans (Mollick & Assefa, 2013).

4.1.6. COVID-19

COVID-19, caused by the SARS-CoV-2 virus, is a respiratory illness that emerged in Wuhan, China, towards the end of 2019 and quickly spread globally due to its highly contagious nature. The illness rapidly transformed into a pandemic, which led to a global health crisis, significant economic contractions, and severe restrictions on travel and trade. It also shifted education, work, and social interactions largely to online platforms, which led to significant changes in business models and working environments across many sectors (McKibbin & Fernando, 2020).

International and local travel restrictions led to a sharp decrease in air travel demand. Many airlines went bankrupt or sought financial aid. Flight numbers dropped, airports were left empty, and there was a significant loss of revenue coming from tourism. This

situation forced a reevaluation and restructuring of business models within the aviation sector (Sun et al., 2022).

The COVID-19 pandemic had a significant impact on the aviation sector, leading to a tragic decline in passenger traffic. In April 2020, passenger traffic fell by 96% compared to the same month in 2019 (Bureau of Transportation Statistics, 2020), with the remaining 4% largely consisting of flights organized to repatriate citizens stranded abroad due to quarantine measures. This level of decline was unprecedented in the history of aviation, marking COVID-19 as the most impactful external shock the sector has ever faced (Figure 4)



Fig.1 - World passenger traffic evolution, 1945–2022

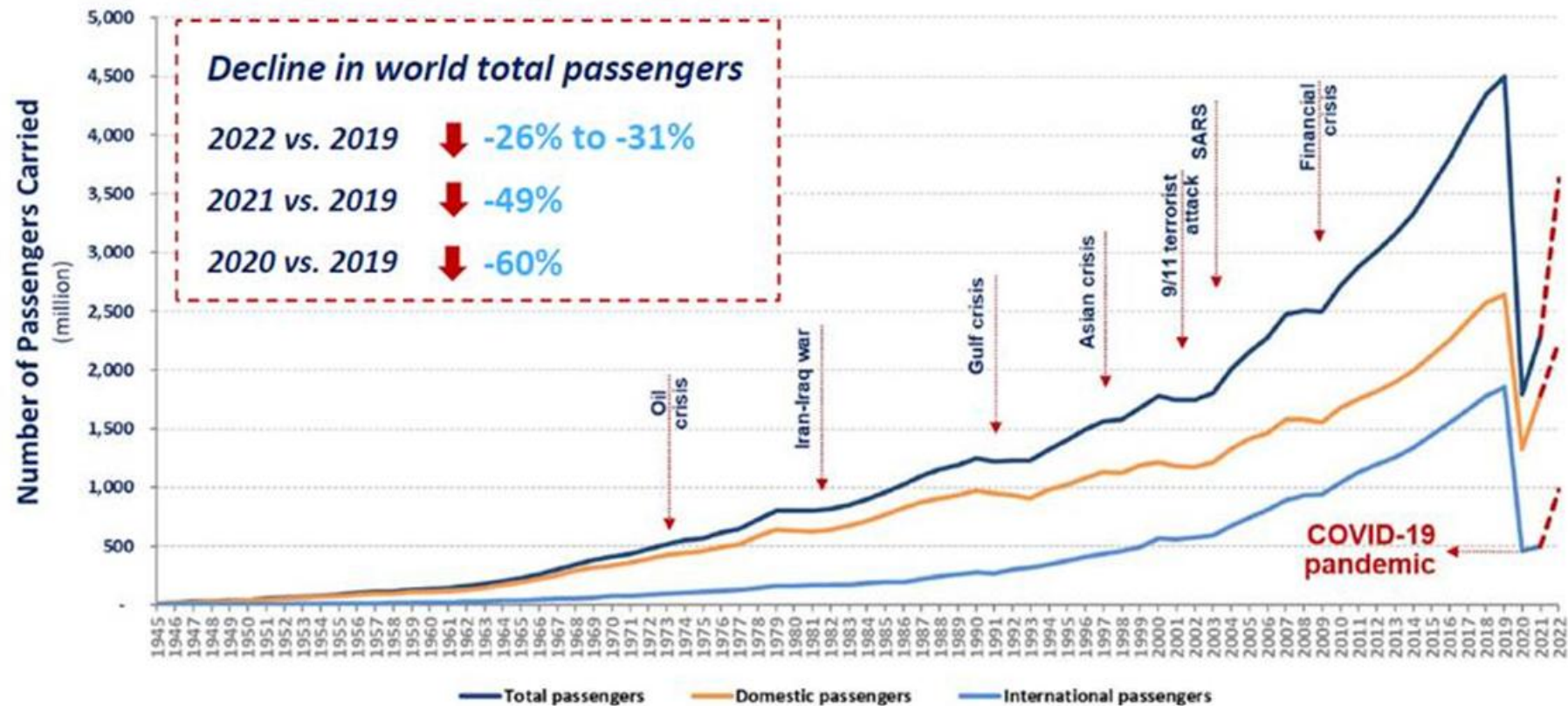


Figure 4.2. World Passenger Traffic Evolution 1945-2022

Referece: Uniting Aviation, 2022

Key impacts of COVID-19 in the aviation sector (Hopanci et al., 2021):

- **Massive Revenue Losses:** With the grounding of flights and plummeting passenger numbers, airline revenues drop drastically, pushing many of them to the edge of financial collapse.
- **Shift in Consumer Behavior:** The pandemic altered consumer expectations and behavior, which led to increased demand for flexible booking options, full refunds, and enhanced health and safety protocols.
- **Reduced Passenger Demand:** As companies and individuals cut back on expenses, discretionary spending on travel was significantly reduced. This decline was faced at all classes of travel but was particularly significant in premium travel, which typically generates higher profit margins for airlines.
- **Financial Instability:** After COVID, a general decline in the profitability of commercial airlines was observed all over the world (Aksoy & Kartoglu, 2023). Many airlines struggled to maintain liquidity and manage debt as revenues fell. The inability to access credit for operational and capital financing further worsened the financial struggle.

In response to the radical decrease in travel demand, airlines grounded many of their aircraft or took them out of service, which subsequently reduced the demand for maintenance. Government aid became essential for the survival of the sector, in the form of payroll support, rent reliefs, and other financial assistance. National aviation authorities also provided temporary exemptions from certain regulatory requirements to assist the industry (Deveci et al., 2022).

Businesses acted rapidly to mitigate financial losses and to survive until demand could recover. This rapid response included (Kökény et al., 2022):

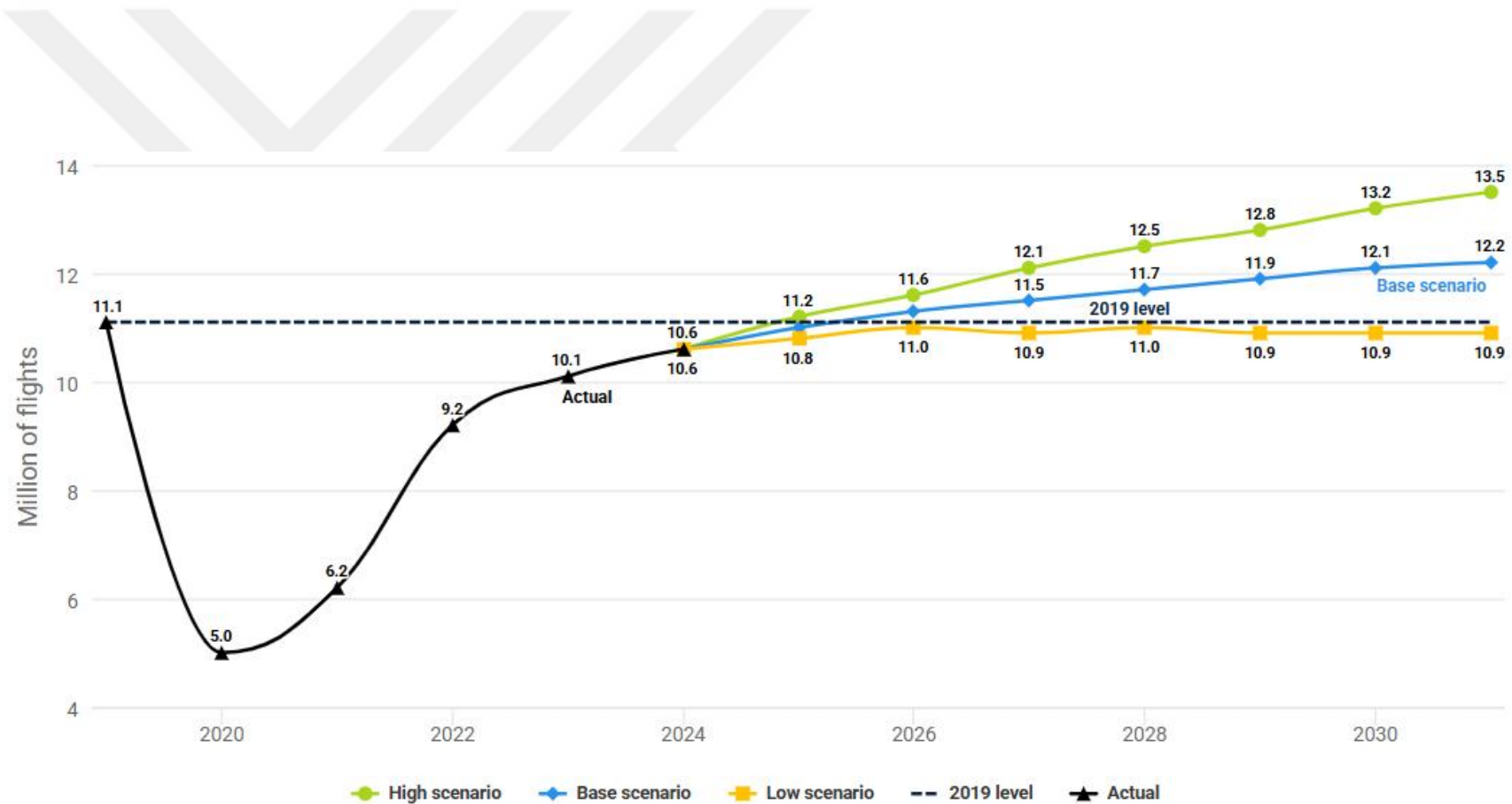
- **Capital Preservation Measures:** Deferring or cancelling non-critical capital expenditure projects, such as postponements in new aircraft deliveries or halting upgrades to facilities.
- **Enhanced Health and Safety Protocols:** Implementing strict health and safety measures to reassure the traveling public and comply with new health

guidelines. These measures are: increased cabin cleaning, mandatory mask-wearing, and adjustments to service protocols to minimize contact. Improved air filtration systems have also been introduced to reduce virus transmission risks.

- **Shift in Operational Focus:** Many airlines shifted focus towards cargo operations to address the revenue decrease due to the downturn in passenger services. Cargo flights became a critical source of revenue, as the demand for the transportation of medical supplies and other essential goods rose globally (Irmak & Pelit, 2022).
- **Utilization of Technology:** Adoption of digital technology to reduce operational costs and enhance customer service, such as contactless check-in processes, biometric screenings, and the use of artificial intelligence to predict changes in passenger demand patterns.
- **Operational Adjustments:** Airlines had to quickly adjust operations, including suspending routes, reducing flight frequencies, and implementing strict health and safety measures to protect passengers and crew. They were forced to make significant cuts to their operations, including reducing the number of flights, retiring older, less efficient aircraft earlier than planned, and delaying or canceling orders for new aircraft (Kökény et al., 2022).
- **Financial Strategies:** To survive the financial impact, airlines looked for government support, made use of furlough schemes, cut salaries, and in some cases, restructured debt (Koç, 2022).
- **Long-term Strategic Changes:** Airlines began reconsidering their long-term strategies, focusing more on cargo services during the downturn in passenger travel and rethinking the size and composition of their fleets to adjust to changing market conditions (Sun et al., 2022).
- **Cost-Cutting Measures:** To survive the downturn, airlines implemented strict cost-cutting measures, including layoffs, wage cuts, and other expense reductions. They also renegotiated contracts with suppliers and vendors to lower costs.
- **Strategic Realignments:** The crisis forced airlines to reassess their strategic plans. Many of them shifted focus from expansion to consolidation, improving

operational efficiency and enhancing the profitability of existing routes and services.

As of 2024, the aviation industry has demonstrated significant recovery from the impacts of the COVID-19 pandemic. EUROCONTROL's latest forecast indicates that the number of flights in Europe had reached 10.6 million in 2024, representing 96% of the 2019 pre-pandemic levels. This recovery level changes with the International Air Transport Association's (IATA) projections globally, which anticipate global passenger numbers to reach approximately 4.96 billion in 2024, surpassing 2019 figures and achieving a 103% recovery. These developments show the aviation sector's strong rebound, increasingly restoring its operational capacity and customer base to pre-pandemic levels (EUROCONTROL, 2025b; IATA, 2024; Investopedia, 2024; Figure 4.3).



* Europe = ECAC 44 Member States

Figure 4.3. Eurocontrol Actual and Future Traffic Count in Millions

Referece: EUROCONTROL, 2025b

This recovery is supported by various adaptations within the industry. These adaptations include the implementation of enhanced health and safety measures, shifts in market strategies like low-cost service offerings, and the integration of more robust digital solutions to improve efficiency and customer experience. These strategic adjustments are critical as they not only address changing consumer preferences but also enhance operational flexibility.

One example of these strategic shifts has been particularly notable. For example, due to the increased demand for low-priced tickets and a reduction in customer interaction during the pandemic, Turkish Airlines restructured its low-cost internal brand, AnadoluJet (Taşçı & Yalçınkaya, 2015) into a separate company named AJET (Business Traveller, 2023). The objective is to perform low-cost operations under this distinct entity to reduce costs effectively (Barutçu & Çolakoğlu, 2024).

The COVID-19 pandemic significantly impacted the aviation sector, affecting various airlines to differing extents.

Turkish Airlines (THY) has demonstrated a notable recovery from the downturn caused by the COVID-19 pandemic. As of September 2024 operational reports, THY has not only rebounded but has also surpassed significantly its pre-pandemic operational metrics as of ASK, RPK, flight numbers, passenger numbers, etc, which is a significant indicator of recovery and growth. This recovery is a reflection of the airline's strategic adaptations during and after the pandemic, including optimizing its route network, enhancing cargo operations against decreased passenger demand, and implementing robust health and safety protocols to reassure passenger confidence. The increase in flight numbers suggests effective management practices and an agile response to the fluctuating demands of the global travel market (THY, 2024; Figure 4.4).

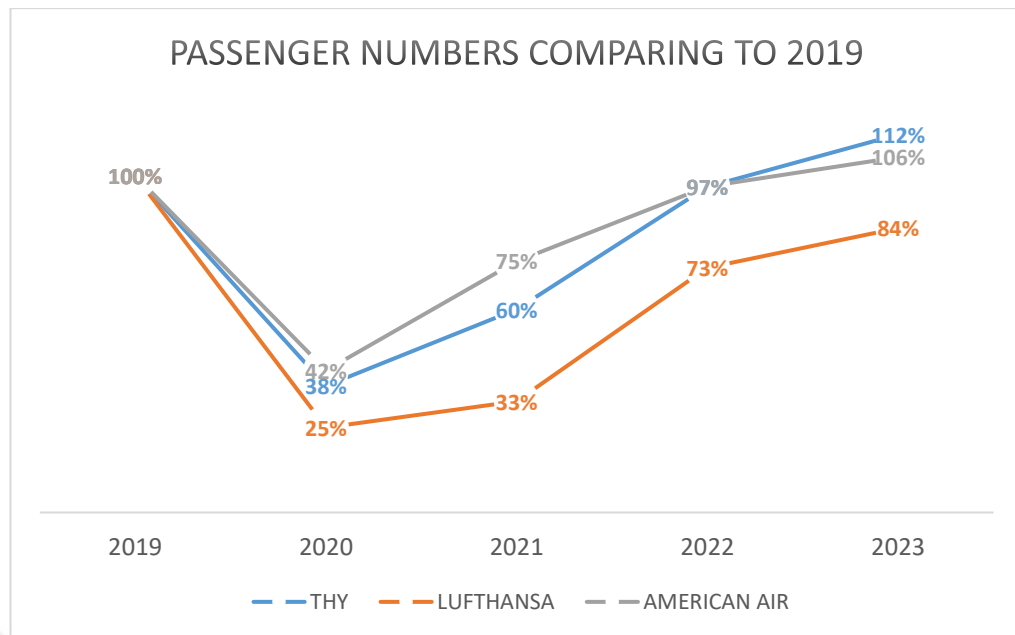


Figure 4.4. Passenger Numbers of Selected Airlines Compared to 2019

Referece: Created by the author using company operational data.

One example of these strategic adaptations is that THY did not introduce layoffs but implemented wage cuts and unpaid leaves for its employees. By doing this, THY kept its employees within the company. When flight restrictions eased and the effects of the pandemic decreased, THY was ready to answer increasing passenger demand. This way, THY was able to capture recovering passenger demand after the pandemic, earlier than its competitors.

As of September 2024, operational reports of Lufthansa have demonstrated a recovery from the COVID-19 pandemic's significant impacts on global airline operations. By the end of 2024, Lufthansa reported a steady increase in passenger numbers and flight operations, approaching the levels seen in 2019, but still below them. The probable cause may be that the number of flights in Europe is not yet able to reach pre-pandemic levels, according to Eurocontrol's traffic reports. One other aspect may be the increasing number of flights that low-cost airlines offer in Europe, compared to the pre-pandemic level. Passenger demand may shift from full-service airlines to low-cost carriers in the economic environment after the pandemic (EUROCONTROL, 2025a; Lufthansa, 2024; Figure 4.4).

Despite experiencing financial difficulties due to the pandemic, most American airlines avoided bankruptcy and received significant financial support from the government. This aid helped maintain liquidity for the major airlines.

American Airlines has made substantial progress in its recovery from the devastating effects of the COVID-19 pandemic, which had led to unprecedented operational and financial challenges across the global aviation industry. Comparing its current operations to 2019, American Airlines has just reached the operational volume of the pre-pandemic era. Although recovery levels between airlines in the USA aviation vary significantly, American Airlines' operational metrics, such as ASK, RPK, flight numbers, and passenger numbers, are at the 2019 levels. This growth is credited to strategic enhancements in operational efficiency, suitable addressment of changing customer demand after the pandemic, and a focus on both domestic and international markets (American Airlines, 2024; Figure 4.4).

As can be concluded from the above, although global recovery levels in the aviation industry are at the pre-pandemic levels, recovery levels vary between regions. It is anticipated that the aviation sector will take approximately a couple of years to fully recover from the effects of COVID-19 for all regions. This study will examine the operational performance aspect of this recovery process and investigate its impact on stock prices, aiming to provide perceptions and benefits to academics, investors, and managers.

CHAPTER V

THE IMPACT OF PERFORMANCE OF FULL-SERVICE CARRIER AIRLINES ON STOCK PRICES DURING COVID-19

5.1. Subject and Purpose of the Research

This study aims to examine the impact of operational performance indicators of full-service airlines on their stock prices during and after the COVID-19 pandemic. The study aims to provide current data that can be used in strategic decision-making processes, thereby aiding companies and stakeholders in the sector in making more informed decisions.

By analyzing the aviation industry's response to the pandemic, such as adjustments in flight operations, passenger numbers, etc., this study seeks to offer valuable insights into how airlines managed to overcome the challenges introduced by the pandemic and how these methods affected the stock prices of companies (Koç, 2022).

The findings of this study will not only help clarify the sector's resilience and adaptability but also guide strategic planning and investment decisions in the post-pandemic era. It aims to close the gap between theoretical knowledge and practical implementation, while enhancing the strategic capabilities of aviation industry stakeholders (Evans et al., 2011).

5.2. Importance of the Research

The measurement of company performance provides investors the ability to identify companies with potential for value creation and make informed investment decisions. Stock prices are shaped not only by a company's performance but also by market expectations and other external factors (Dehuan & Jin, 2008).

Examining the changes in the aviation sector during the pandemic is crucial for industry professionals, investors, and policymakers. The benefits of such research can be summarized as follows (Flouris & Oswald, 2006):

- **Strategic Planning:** Understanding how the airline industry was affected during the pandemic helps companies better prepare for future crises. This forms the foundation for developing risk management strategies and enhancing resilience against potential shocks.
- **Operational Flexibility:** Analyzing the effects of COVID-19 on airlines aids in assessing companies' operational flexibility and adaptability during a crisis. This is critical for ensuring the sustainability of operations in similar future occasions.
- **Understanding Market Dynamics:** Insights into changes in travel demand, consumer behaviors, and preferences during the pandemic allow airlines to adjust their marketing and service strategies more effectively.
- **Investment Decisions:** Performance data during the pandemic provides investors with valuable insights into which airlines are more resilient to crises and which are not. This helps in making informed investment decisions.
- **Policy and Regulation Development:** The research can help governments and regulatory bodies develop appropriate policies and regulations for the aviation industry. Challenges that emerged during the pandemic can help future policy decisions (Johnson & Anderson, 2004).

Researching the recovery of the aviation industry from the pandemic is fundamental to understanding the sector's future success, overall health, and resilience, in addition to the benefits mentioned above.

5.3. Restrictions of the Research

The scope of the research focuses on Full-Service Carriers (FSCs). Future studies could expand to include other business models within the aviation sector, such as low-cost carriers (LCCs), cargo airlines, and charter services, which could provide insights into different dynamics and operational strategies.

In this study, ASK, RPK, Passenger Number, Flight Number, and Load Factor were considered primary independent variables. However, macroeconomic factors such as fuel prices, interest rates, exchange rates, or global economic growth rates have not been included in the model. These excluded variables could also significantly influence stock prices.

Although Ridge regression has been employed due to issues of multicollinearity, this method tends to decrease the effect of independent variables, potentially understating certain relationships.

The distribution of error terms is found to be non-normal, and autocorrelation problems are observed in specific models. Therefore, robust regression techniques have been applied to correct the standard errors.

Another limitation of this study is the timeframe of the data collected, which spans from 2019 to 9M2024. A study done after airlines fully recover to pre-pandemic levels could give more useful results, which show the long-term effects of the pandemic and how well recovery strategies worked.

Additionally, the study includes airlines such as Turkish Airlines (THY), Lufthansa (LHA), and American Airlines (AAL), which represent regions in Eastern Europe, Europe, and North America, respectively. Future research could be enhanced by including airlines from other regions, especially from Asia, to make a broader analysis.

The COVID-19 pandemic period, specifically from March 2020 to September 2021, has been included in the model as a dummy variable. However, considering the dynamic nature of the pandemic's impact, a more detailed modeling of structural breaks might be necessary to catch varying effects during different time periods.

Monthly data have been used in this study, resulting in a total of 69 observations. The relatively limited size of the dataset may constrain the statistical power of certain models in time-series analysis.

The airline industry is sensitive to government policies and regulations. Factors such as governmental incentives, taxes, or regulatory changes in the aviation sector have not been considered in this study.

5.4. Literature Review

- **Research that focuses on the operational aspects of airlines:**

Behn & Riley Jr. (1999) examined whether non-financial information can help predict financial performance in the U.S. airline industry. The study used industry metrics like on-time performance, mishandled baggage, ticket oversales, and in-flight service as indicators of customer satisfaction. Results showed that non-financial measures such as customer satisfaction, load factor, market share, and available ton miles are closely related to airline revenues, expenses, and operating income. The findings suggested that non-financial data can be a valuable tool for forecasting short-term financial outcomes.

Liedtka (2002) investigated whether non-financial performance measures (NFPMs) give extra useful information about airline companies, other than financial data. The study used data from 10 U.S. airlines between 1988 and 1998. Results showed that NFPMs—like customer complaints, flight safety, and efficiency—provide different insights that financial measures do not offer. The study supports using both financial and non-financial data to better understand company performance.

Tsikrikis (2007) conducted a longitudinal analysis of the U.S. airline industry to understand the relationship between operational performance, strategic focus, and profitability. The study revealed that "focused" airlines, which organize their operations around a specific market or service, showed a stronger connection between operational efficiency and profitability compared to full-service airlines. In contrast, for full-service carriers, profitability was more significantly influenced by capacity utilization rather than operational efficiency.

In another study by Aksoy et al. (2022), it was revealed that increasing operational efficiency in the aviation sector also leads to various positive effects (shortening flight times, reducing fuel costs, optimizing routes, ensuring sustainability, etc).

Yaghi (2015) examined how financial performance in the airline industry can be assessed using both conventional financial ratios and aviation-specific metrics. He analyzed liquidity, activity, profitability, and leverage ratios of 17 international airlines between 2011 and 2013. The study highlights the industry's unique financial behavior and evaluates whether standard financial rules apply. Airline-specific measures, such as kilometers traveled, passengers carried, and load factors, are used to understand operational growth and efficiency. It found that combining these traditional and industry-specific methods allows for a comprehensive comparison.

Dayi (2020) investigated how operating ratios influence the market value of European airlines. Using panel data analysis, the study evaluated variables such as asset turnover, inventory turnover, accounts receivable turnover, financial leverage ratio, and stock price. The findings revealed that firm value is positively impacted by accounts receivable turnover and asset turnover. On the other hand, it is negatively affected by inventory turnover and financial leverage. The research underscores the importance of financial productivity and effective asset use for enhancing firm value.

Bas & Aksoy (2022) examined the impact of cargo revenues and ancillary revenues on net income for three full-service airlines: Turkish Airlines, American Airlines, and Delta Air. Data from 2014-Q1 to 2019-Q4 were analyzed using a logarithmic econometric model. The study concluded a positive correlation between cargo revenue, ancillary revenue, and net income. The study also revealed that increases in cargo revenue and ancillary revenue increase full-service airlines' net income. Additionally, it was indicated that ancillary revenues provide a significant source of revenue for those airlines (Aksoy & Bas, 2021).

- **Research that focuses on the factors affecting stock price:**

Lam (2002) examined how financial metrics like firm size, book-to-market equity ratio, and earnings-price ratio influence stock returns. Using data from the Hong Kong

Stock Exchange between 1984 and 1997, the study found that these three variables capture variations in average stock returns, while traditional metrics such as market beta don't. The research also demonstrated that book leverage and market leverage have weaker explanatory power compared to the primary metrics.

Tudor (2008) investigated whether firm-specific financial factors can predict future stock returns on the Romanian stock market between 2002 and 2008. The analysis implemented panel regression models. The study found that company size and the earnings-to-price (E/P) ratio are the strongest predictors of future returns. Company size has a negative relationship with returns, while E/P has a strong positive effect. Other variables such as financial leverage, ROA, and ROE have minor but statistically significant impacts. Market beta and book-to-market ratio show little or no explanatory power. These findings suggest market inefficiency and support the use of firm-level fundamentals indicators in return forecasting.

Subing et al. (2017) examined how internal factors, such as price-to-earnings ratio and return on assets, and external factors, such as inflation and oil prices, influence stock pricing in Indonesia's consumer goods industry. Using data from 2008 to 2015 from 18 companies, the research found that internal factors and oil prices positively impact stock prices, whereas inflation has a negative effect.

Öztürk & Karabulut (2018) investigated the influence of financial ratios on stock returns in the Istanbul Stock Exchange between 2008 and 2016. Using panel data analysis, the authors found that the Earnings-to-Price (E/P) ratio and net profit margin significantly predict stock returns; in contrast, the current ratio doesn't. The findings suggest that stocks with higher E/P ratios and profit margins produce higher returns in the following periods.

Alıcı (2020) examined how internal financial factors affected the stock prices of 28 airline companies from 2005 to 2018. Using panel data and Panel VAR analysis, they find that total assets (firm size) positively influence stock prices, while financial leverage negatively affects them. The study also showed that liquidity and beta value have causal effects on stock price changes; however, their direct relationships are

weaker. The authors suggested that airline companies can boost stock value by expanding their asset base and managing leverage and liquidity efficiently.

Unal et al. (2022) studied how COVID-19 vaccination rates affected stock market performance in 49 countries listed in the MSCI Developed and Emerging Markets indices. The countries were grouped by how soon they reached 10%, 50%, and 75% vaccination levels. The results showed that countries that reached 10% and 50% vaccination levels earlier had better stock market returns and less market volatility. However, reaching a 75% vaccination level did not show a significant difference. These findings were in effect for both developed and developing countries. The study suggests that faster vaccination programs help not only public health, but also bring positive effects to the economy and financial markets.

- **Research that focuses on the external shocks and crises affecting airline businesses:**

Njegovan (2006) analyzed whether shocks to air passenger traffic in the UK are permanent or temporary, using time series data from 1960 to 2003. The study finds that most shocks—such as wars, terrorist attacks, and epidemics—are transitory, with traffic returning to its long-term growth trend. However, the 1974 oil crisis had a lasting impact on growth rates. Compared to other countries, the UK, Germany, and Australia show trend-reverting indications, while the U.S. and Canada do not. These results suggested that long-term air traffic forecasts in the UK remain reliable despite short-term disruptions.

Mantin & Wang (2012) investigated how operations strategy, productivity, and service quality affect airline profitability before and after the 9/11 attacks. Using data from U.S. airlines between 1995 and 2007, they found that all three factors—strategy, productivity, and service—significantly impacted profitability before 9/11. However, after 9/11, only operations strategy and productivity remained significant. Service quality lost its predictive power, possibly due to passengers' reduced expectations under tighter security measures. The study also showed that load factor and aircraft utilization became more crucial after 9/11, especially for full-service carrier airlines recovering faster than other business-focused airlines.

Wang (2013) examined how major global crises affect the volatility of stock prices in the airline industry. Using the GARCH model, the study analyzes data from 16 international airlines over the period of 1996–2010. Significant crises, such as the Asian financial crisis, the 9/11 terrorist attacks, the SARS outbreak, and the 2007 global financial crisis, were included as variables. Findings reveal that these events significantly increase stock price volatility, depending on regional and airline-specific factors. For example, the 9/11 attacks had a significant impact on U.S. airlines, while Asian airlines encountered greater volatility during the SARS outbreak.

Kathiravan et al. (2019) investigated the connection between fluctuations in crude oil prices and the stock prices of six major Indian airlines over an 11-year period (2007–2018). Using statistical methods like the Granger Causality Test and correlation analysis, the study identified causal relationships between oil price changes and airline stock returns. Results showed that changes in crude oil prices impact the costs and cash flows of airlines, which, in turn, affect their stock prices. Specific crude oil prices, such as Brent and WTI, presented significant causal effects on airlines like IndiGo, Jet Airways, and SpiceJet.

- **Research that focuses on the effect of COVID-19 on airline businesses:**

Yiğit & Canöz (2020) examined how airline stocks in 14 European countries reacted to the COVID-19 pandemic using event study methodology. They analyzed 38 airline stocks across multiple event windows surrounding March 11, 2020, the day the WHO declared the pandemic. The findings showed significant negative abnormal returns in both short and long windows, especially in the -50 to +50 period. The reactions varied by country, with some markets reacting immediately, while others showed delayed responses. The study concluded that the pandemic had a strong and measurable impact on airline stock performance in Europe.

Carter et al. (2022) explored how the pandemic impacted stock performances across the airline, hotel, and tourism sectors. The study found that larger firms with better cash reserves and higher market-to-book ratios suffered less from the pandemic. On the other hand, firms with higher leverage suffered more. Additionally, cash reserves

were found particularly crucial for hotels, which reflects their need for financial liquidity during this crisis.

Nguyen et al. (2022) examined how the pandemic affected global airline stocks. The study indicated severe initial market value drops and increased volatility in stock prices, although these effects were temporary. The research used data from 42 airline companies across various markets and found that not all stocks showed higher exposure to systematic risks.

Fan (2023) explored the relationship between the COVID-19 pandemic and U.S. airline stock performance by analyzing ten key pandemic-related events between January 2020 and August 2022. It focused on seven airline stocks, including JetBlue, Delta, and United Airlines, to assess how their prices reacted to significant events like the declaration of the pandemic and vaccine developments. Findings show that airline stock prices reacted quickly to positive or negative news during the event windows, consistent with the semi-strong form of the Efficient Market Hypothesis. Events such as the lifting of mask mandates or the announcement of new virus variants significantly influenced stock prices, while investor reactions vary based on the nature of the events.

- **Research directly related to this study:**

Riley et al. (2003) examined how non-financial performance metrics, such as customer satisfaction, capacity utilization, and load factors, impact stock prices in the airline industry compared to traditional financial measures like earnings per share. The findings showed that non-financial factors, like higher load factors and increased capacity, are positively linked to stock performance; on the other hand, customer dissatisfaction negatively affects returns. Non-financial metrics provided more useful insights into stock price movements than traditional financial data.

Turturea & Turcu (2015) examined how non-financial indicators can improve performance measurement in the airline industry. By analyzing data from 32 international airlines (2006–2013), they found that indicators like load factor and available seat kilometers significantly affect stock prices. Financial metrics such as pretax return on assets and current ratio also show a strong relationship. The study

concludes that combining financial and non-financial data provides a more accurate view of company performance.

Alıcı (2020) investigated the factors influencing stock prices in the airline industry by examining operational, financial, and macroeconomic variables. The study used data from both traditional and low-cost airlines between 2005 and 2018. It utilized panel data analysis and causality tests, such as the Toda-Yamamoto and Hatemi-J asymmetric causality methods, to discover the relationships between these factors and stock prices. The findings revealed that operational metrics like load factors (LF), revenue passenger kilometers (RPK), and cost per available seat kilometer (CASK) significantly affect stock prices, while higher efficiency and profitability lead to better performance. Financial variables, including liquidity, firm size, and financial leverage, are also critical in determining stock prices. Additionally, macroeconomic factors such as fuel prices, exchange rates, and interest rates have substantial impacts on stock prices, which demonstrates the sensitivity of the airline industry to external economic conditions. The research emphasizes that airline companies can enhance their stock performance by improving operational efficiency, reducing costs, and managing financial risks effectively.

Samson (2021) explored the connection between operational performance and stock prices in the airline industry, using Turkish Airlines as a case study. It analyzed data from 2011 to 2020 and examined variables such as flight numbers, available seat kilometers (ASK), revenue passenger kilometers (RPK), load factors, passenger numbers, and cargo quantities. The results showed that there is a one-way causal relationship between cargo quantities and ASK and stock prices.

Alıcı & Sevil (2021) analyzed how operational ratios affect stock prices in low-cost airline companies. Using panel data from six airlines between 2005 and 2017, they find that revenue passenger kilometers (RPK) have a significant positive effect on stock prices, while cost per available seat kilometers (CASK) has a significant negative effect. Other indicators like Load Factor (LF) and Operational Profit/Loss (OKZ) show no significant impact. The study highlighted the importance of demand-side and cost-efficiency indicators in evaluating the stock performance of low-cost carriers.

In their later research Alici & Sevil (2022) analyzed the impact of operational performance metrics on the stock prices of traditional airlines using panel data of five carriers between 2005 and 2017. The study found that Revenue Passenger Kilometers (RPK) and Operational Profit/Loss (OPL) have a significant positive effect on stock prices, while Load Factor (LF) and Cost per Available Seat Kilometer (CASK) have a negative impact. The authors concluded that airlines should focus on increasing revenue and managing costs to improve stock performance. Their findings supported previous studies emphasizing the importance of non-financial indicators in stock price prediction.

5.5. Data Set

The study utilizes monthly operational data from airlines. This frequent data allows for a closer and more timely examination of how various factors influence operational performance month-to-month. This approach offers insights that quarterly or annual financial reports may not provide.

For the dataset used in this study:

- Lufthansa's data has been gathered from the Investor Relations page on the company's website (Lufthansa, 2024).
- Turkish Airlines' data is also obtained from the Investor Relations section of their website (THY, 2024).
- Data for American Airlines has been sourced from the United States Department of Transportation (DOT)'s Transportation Data website under the aviation data section. These data are published with mile units. In order to standardize data within the research, American Airlines data was converted to kilometers (U.S. Department of Transportation, 2025).
- Stock price data is acquired from Refinitiv (formerly known as Thomson Reuters) Eikon Datastream. The monthly average stock price is calculated and analyzed together with the monthly operational data. Stock price data was also converted to USD in order to standardize data within the research.

5.6. Descriptions of the Variables Used in the Econometric Model

For the econometric analysis of this study, ASK, RPK, Load Factor, Passenger Numbers, and Flight Numbers are used as independent variables for THY, Lufthansa, and American Airlines. Stock prices of each airline are used as the dependent variable. A dummy variable to indicate the effects of COVID-19 is also used. Table 5.25.2. shows these variables:

Table 5.2. Variables Used in the Analysis

Variable Symbol	Explanation	Calculation
THY_ASK	Available Seat Km for THY	Flight Distance (km) x Number of Seats Available
THY_RPK	Revenue Passenger Km for THY	Flight Distance (km) x Number of Paying Passengers
THY_LF	Load Factor for THY	RPK/ASK
THY_PAX	Passenger Number for THY	Passenger Number
THY_FN	Flight Number for THY	Flight Number
THY_USD_SP	Stock Price of THY in USD	Stock Price
LHA_ASK	Available Seat Km for Lufthansa	Flight Distance (km) x Number of Seats Available
LHA_RPK	Revenue Passenger Km for Lufthansa	Flight Distance (km) x Number of Paying Passengers
LHA_LF	Load Factor for Lufthansa	RPK/ASK
LHA_PAX	Passenger Number for Lufthansa	Passenger Number
LHA_FN	Flight Number for Lufthansa	Flight Number
LHA_USD_SP	Stock Price of Lufthansa in USD	Stock Price
AAL_ASK	Available Seat Km for American Airlines.	Flight Distance (km) x Number of Seats Available

Table 5.2. (cont.)

AAL_RPK	Revenue Passenger Km for American Airlines.	Flight Distance (km) x Number of Paying Passengers
AAL_LF	Load Factor for American Air.	RPK/ASK
AAL_PAX	Passenger Number for American Airlines.	Passenger Number
AAL_FN	Flight Number for American Airlines.	Flight Number
AAL_USD_SP	Stock Price of American Airlines in USD	Stock Price
Dummy_Pandemic	Dummy variable for the COVID-19 pandemic period, between March 2020 and September 2021	

5.7. Research Model

The equation of the research model is depicted below. In the equation, ASK, RPK, PAX, FN, and LF are determined as independent variables, and Stock Price is defined as the dependent variable. Also, a dummy variable for the pandemic period is added to the equation.

$$\Delta \log(SP) = \Delta \log(ASK) + \Delta \log(RPK) + \Delta \log(PAX) + \Delta \log(FN) + \Delta LF + Dummy_{Pandemic}$$

In the equation, “ Δ ” indicates that the first-level difference of the related variable is used, and “log” indicates that a logarithmic transformation is applied.

5.8. Hypothesis of the Research

Panel data analysis, dynamic panel models, and time-series analyses were employed to analyze the determinants of airline companies' stock prices. Hypotheses have been developed to investigate how airline operational performance indicators influence stock prices. Alternative hypotheses are listed as follows:

- H_{A.1}: ASK of airline companies significantly impacts their stock prices.
- H_{A.2}: RPK of airline companies significantly influences their stock prices.
- H_{A.3}: PAX carried by airline companies has a significant effect on their stock prices.
- H_{A.4}: FN operated by airline companies significantly affects their stock prices.
- H_{A.5}: The LF of airline companies causes a significant effect on their stock prices.
- H_{A.6}: The variable reflecting the impact of the COVID-19 pandemic significantly affects airline companies' stock prices.
- H_{A.7}: Airline companies' stock prices are significantly influenced by their historical stock prices.

5.9. Methodology

For the data analysis, the R 4.4.2 software package was used (Güriş et al., 2020). In testing the hypotheses, dynamic panel data models based on panel data analysis (Arellano-Bond and Blundell-Bond GMM estimators) were employed (Yerdelen Tatoğlu, 2013). The dependent variable was defined as the logarithmic change in airline stock prices ($\Delta \log(\text{SP})$). Independent variables included the logarithmic changes in available seat kilometers ($\Delta \log(\text{ASK})$), revenue passenger kilometers ($\Delta \log(\text{RPK})$), number of passengers ($\Delta \log(\text{PAX})$), number of flights ($\Delta \log(\text{FN})$), the change in load factor (ΔLF), and a dummy variable representing the COVID-19 pandemic's impact. The pandemic's effect was modeled explicitly for the period between March 2020 and September 2021.

The study uses a panel data set consisting of three units (airlines) observed over 69 months. Considering the nature of the panel data—with a small number of units (N) and a larger number of time periods (T)—the fixed-effects model was directly chosen. This model checks for unit-specific, time-invariant fixed effects, which allows the analysis to eliminate unobserved heterogeneity effectively. Due to the small number of units (only three airlines), the assumptions of the random-effects model may not hold, and statistical tests like the Hausman test cannot be reliably applied. Therefore, the fixed-effects model was applied to explicitly capture and model the airline-specific fixed effects. This approach is also recommended by B. Baltagi (2020) for panel data analyses with small N and large T.

Levin-Lin-Chu (LLC) and Augmented Dickey-Fuller (ADF) unit root tests were used to assess stationarity of the variables. Non-stationary variables were differenced at first-order to achieve stationarity. Logarithmic transformations were applied to reduce scale disparities and normalize the data. However, the load factor (LF), being a ratio, was excluded from the logarithmic transformation (Pesaran, 2007).

The issue of multicollinearity among independent variables was evaluated using Variance Inflation Factors (VIF). Given the identification of high VIF values and their potential impact on model estimations, Ridge penalization was applied. Moreover, Breusch-Pagan and Breusch-Godfrey tests were conducted to examine the presence of heteroskedasticity and autocorrelation. Due to the detection of heteroskedasticity, models were re-estimated using robust standard errors (Breusch & Pagan, 1980).

Within the scope of dynamic panel models, Arellano-Bond (difference GMM) and Blundell-Bond (system GMM) estimators were applied. Lagged values of independent variables were assigned as instrumental variables, and appropriate lag levels were determined to mitigate autocorrelation problems (Ahmad et al., 2021). According to model results, the Sargan test confirmed the validity of overidentifying restrictions ($p = 1$), while AR(2) autocorrelation tests validated the absence of second-order autocorrelation in residuals. Furthermore, Wald tests indicated that the models were robustly specified ($p < 2.22\text{e-}16$).

Additionally, separate Ridge regression, Autoregressive Distributed Lag (ARDL), Unrestricted Error Correction Model (UECM), and Restricted Error Correction Model (RECM) estimations were performed individually for three airline companies within the time-series analysis, analyzing both short-term and long-term relationships (Liu et al., 2023).

5.10. Empirical Findings

The trend of variables of airline companies is depicted from Figure 5. to Figure 5..

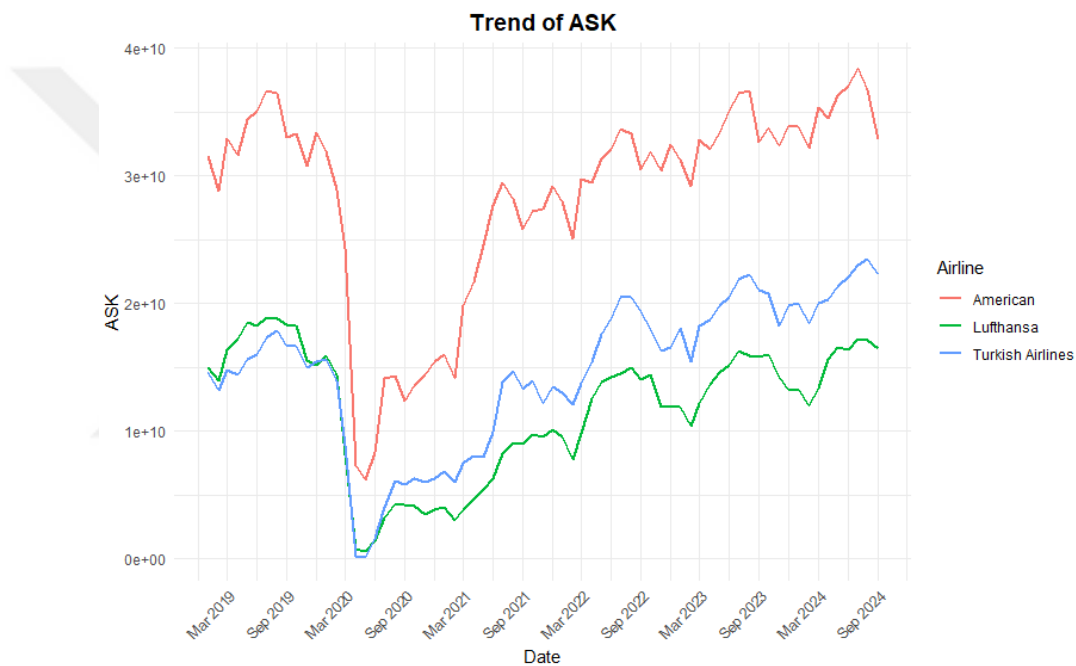


Figure 5.1. Trend of ASK

Figure 5. illustrates the changes in Available Seat Kilometers (ASK) over time for three airline companies. It is observed that American Airlines has distinctly higher ASK values compared to the other two airlines, and this difference persists throughout the analyzed period. However, a sharp decline in ASK values is evident for all airline companies beginning in March 2020, corresponding with the start of the COVID-19 pandemic.

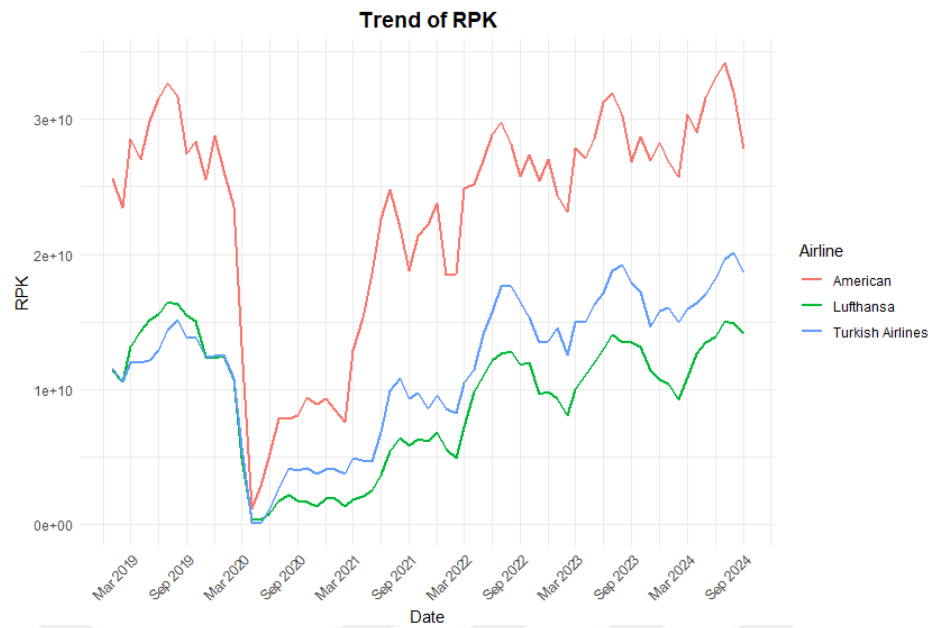


Figure 5.2. Trend of RPK

Figure 5.2 displays the changes in Revenue Passenger Kilometers (RPK) over time for three airline companies. It is apparent that American Airlines has significantly higher RPK values compared to the other two airlines throughout the analyzed period. However, from March 2020 onwards, coinciding with the start of the COVID-19 pandemic, all airline companies experienced a dramatic decline in their RPK values.

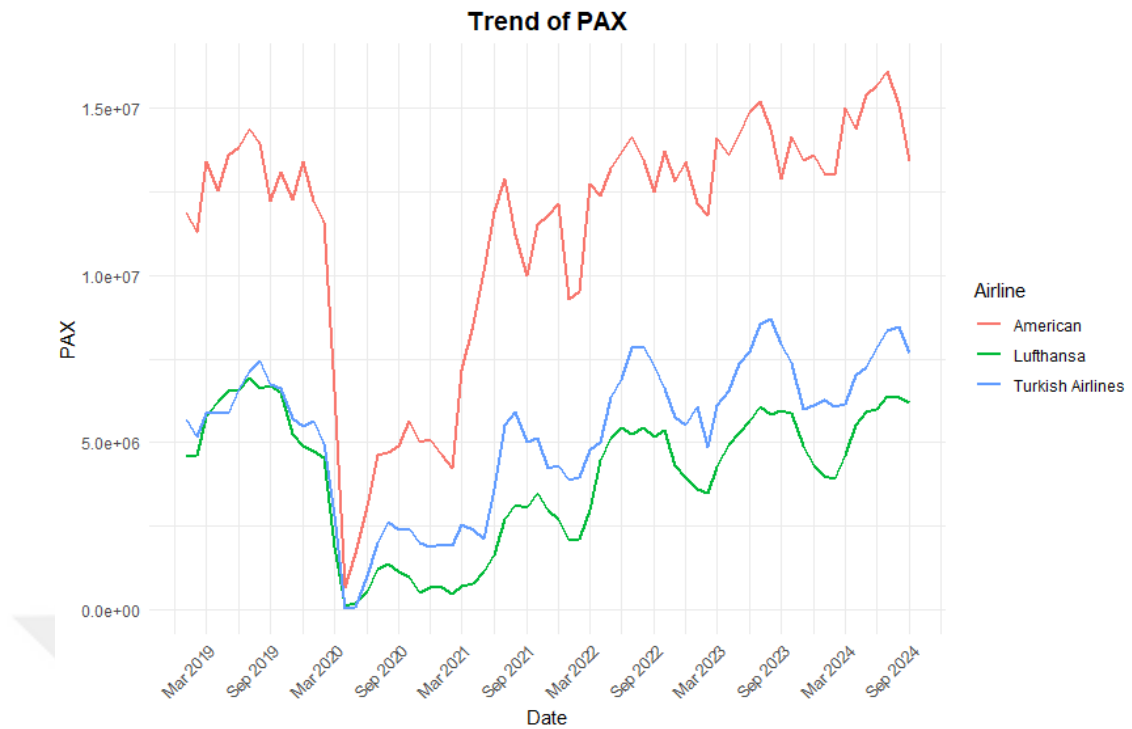


Figure 5.3. Trend of PAX

Figure 5. demonstrates the changes in the number of passengers (PAX) over time for three airline companies. American Airlines stands out with the highest passenger count during the pre-pandemic period. However, following the beginning of the pandemic in March 2020, a dramatic decline in passenger numbers was observed across all airlines. When examining recovery in the post-pandemic period, Lufthansa exhibited a slower increase in passenger numbers. Notably, Turkish Airlines showed a consistent rise in passenger numbers, particularly starting from 2021, indicating a faster recovery compared to other airlines. Lufthansa, despite experiencing fluctuations, generally maintained an upward trend in passenger numbers. American Airlines demonstrated steady progress towards pre-pandemic passenger levels during the post-pandemic recovery period.

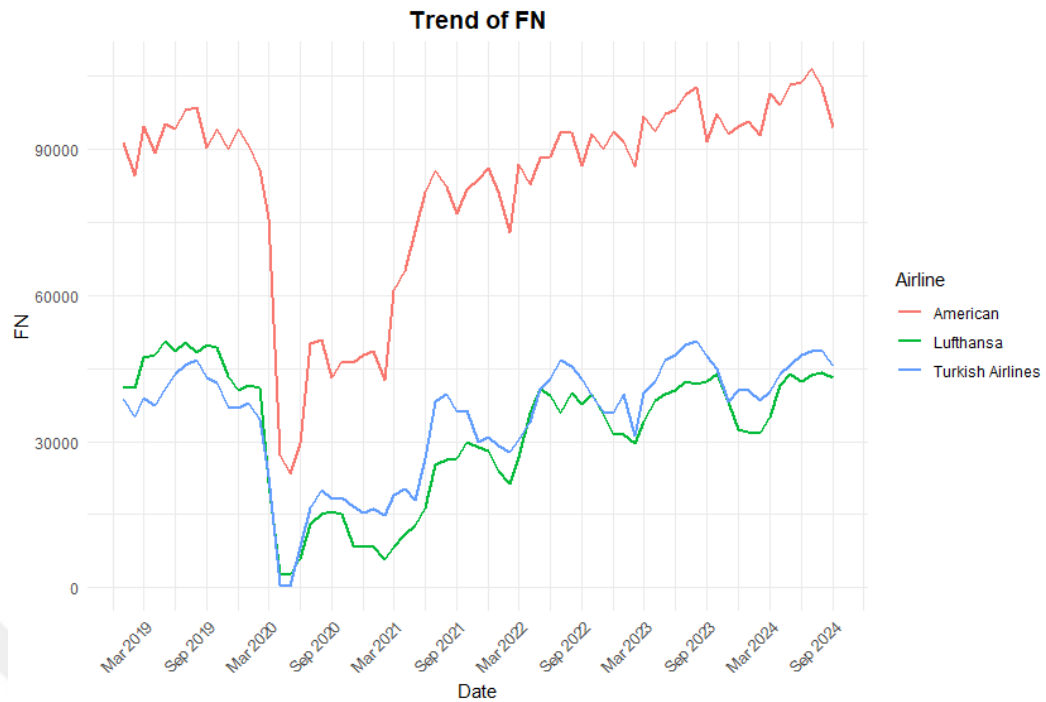


Figure 5.4. Trend of FN

Figure 5. illustrates the changes in the number of flights (FN) over time for three airline companies. American Airlines notably had the highest number of flights in the pre-pandemic period. The pandemic era, beginning in March 2020, resulted in a significant decrease in flight numbers in all airlines, which clearly demonstrates the operational impact of the COVID-19 pandemic on the aviation sector. Specifically, from September 2021 onward, the number of flights has displayed a consistent upward trend for all three airlines.

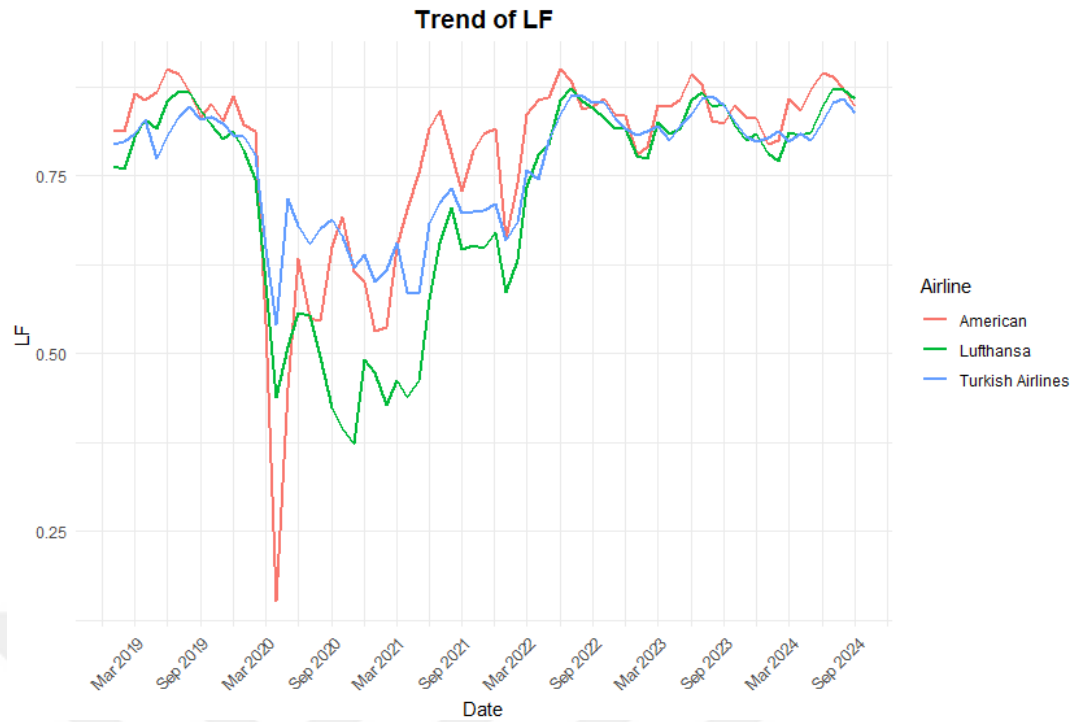


Figure 5.5. Trend of LF

Figure 5. displays changes in Load Factor (LF) over time for airline companies. In the pre-pandemic period, all airlines exhibited high and closely aligned load factor performances. With the arrival of the pandemic in March 2020, a dramatic decline in load factors occurred. During the post-pandemic recovery period, load factors rose rapidly, and by September 2021, airlines gradually succeeded in returning to their pre-pandemic load factor levels.

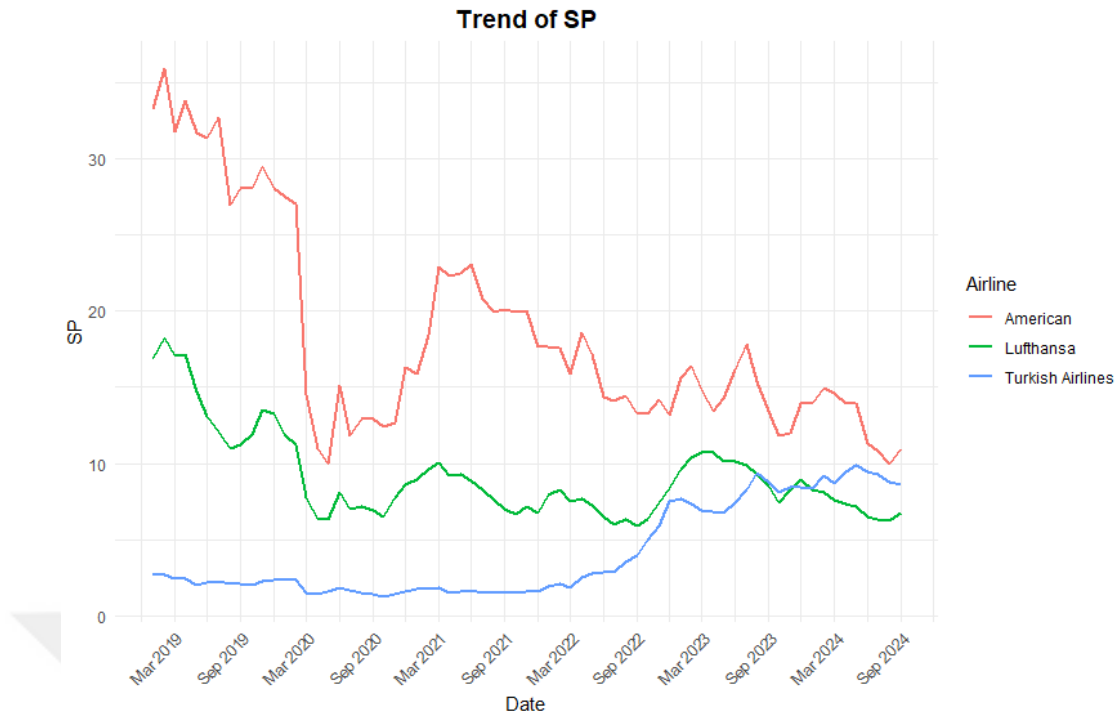


Figure 5.6. Trend of SP

Figure 5. shows that American Airlines, despite having the highest stock price at the beginning of the analysis period, experienced a dramatic decline with the onset of the pandemic. Stock prices decreased significantly in 2020 and failed to recover to pre-pandemic levels during the subsequent recovery period, with only a slow and limited recovery. Lufthansa was similarly but less severely impacted by the pandemic and also failed to recover to pre-pandemic levels. Turkish Airlines, although initially having lower stock prices compared to other airlines, showed a steady upward trend in the post-pandemic period and has surpassed its pre-pandemic valuation by a noticeable margin in 2022, whereas other airlines still appear to struggle to recover their pre-COVID levels at the end of the analysis period of the study.

Based on this information, the period between March 2020 and September 2021 has been identified as significantly impacted by the pandemic. Consequently, this period has been included in the model to represent the pandemic's effect.

The Levin-Lin-Chu test was employed for unit root testing of the variables (Tari, 2015). Due to considerable scale differences among variables, logarithmic transformations were applied to normalize the data. However, since the load factor (LF) is expressed as a ratio, it was excluded from the logarithmic transformation.

Table 5.3. Results of Unit Root Tests

	LLC statistics value	p value	Result
ASK _{log}	-0.033	0.487	Not Stationary
RPK _{log}	-0.054	0.478	Not Stationary
PAX _{log}	-0.068	0.473	Not Stationary
FN _{log}	-0.136	0.446	Not Stationary
LF	-0.255	0.399	Not Stationary
SP _{log}	-1.323	0.093	Borderline Stationary
Δ ASK _{log}	-12.04	<0.001	Stationary
Δ RPK _{log}	-12.801	<0.001	Stationary
Δ PAX _{log}	-12.685	<0.001	Stationary
Δ FN _{log}	-12.534	<0.001	Stationary
Δ LF	-12.224	<0.001	Stationary
Δ SP _{log}	-11.736	<0.001	Stationary

According to the Levin-Lin-Chu (LLC) unit root test results, the p-values for ASK, RPK, PAX, FN, and LF were found to be greater than 0.05, indicating that these variables were non-stationary and contained a unit root. The SP variable had a borderline p-value of 0.093, which was also accepted as non-stationary at a 95% confidence level. Therefore, the test was repeated after taking the first-order differences. The LLC test results with first differences showed p-values smaller than 0.05 for all variables, leading to rejection of the null hypothesis. Hence, it was concluded that the first differences of all variables were stationary and free of unit roots. Accordingly, the assumption of stationarity was satisfied (Karagöz, 2016).

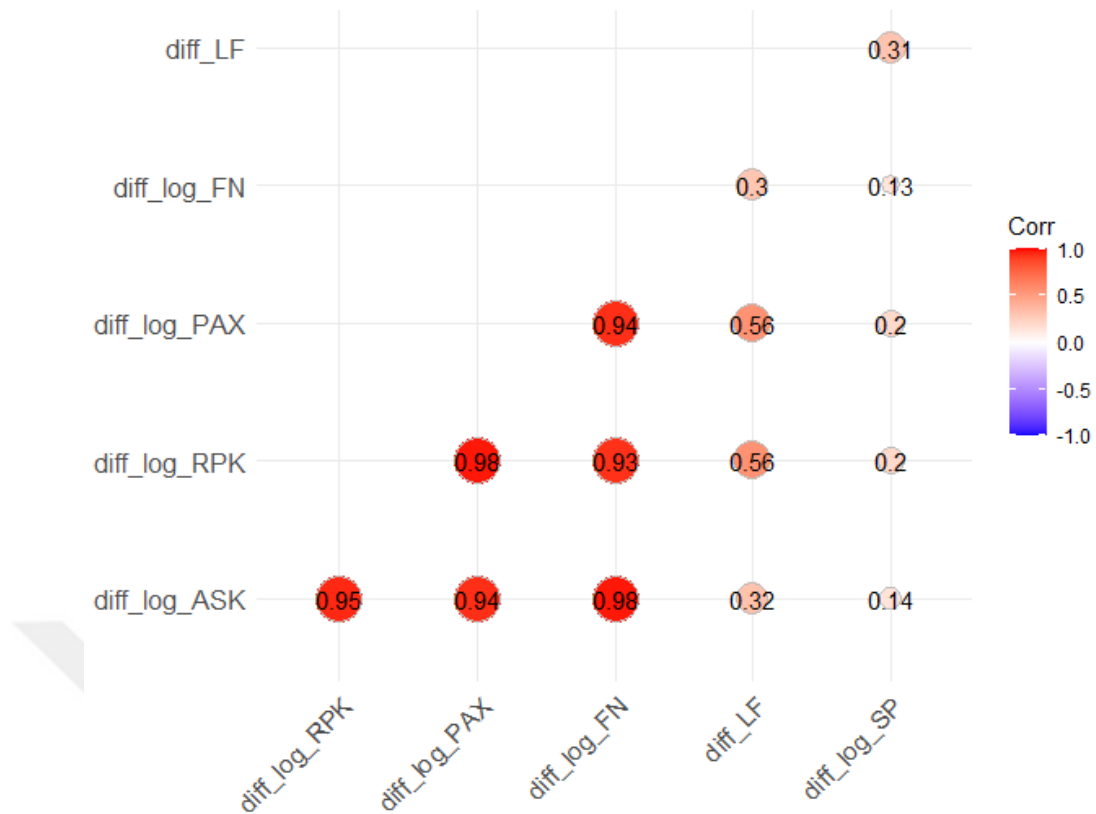


Figure 5.7. Correlation of Variables

According to the correlation graph presented in Figure 5., there are high linear relationships among the variables log_ASK_diff, log_RPK_diff, log_PAX_diff, and log_FN_diff ($r > 0.9$). Particularly, there is a very strong correlation between log_RPK_diff and log_PAX_diff, with a correlation coefficient of $r = 0.98$. These high correlations indicate a multicollinearity issue among the independent variables in the model. The variables LF_diff and log_SP_diff exhibit comparatively lower correlation coefficients with other variables. Therefore, multicollinearity was further investigated by using the Variance Inflation Factor (VIF) (Hsiao, 2003).

Table 5.4. Multicollinearity Test of Independent Variables

Variable	VIF Value
$\Delta \log(\text{ASK})$	123.81
$\Delta \log(\text{RPK})$	142.98
$\Delta \log(\text{PAX})$	84.53
$\Delta \log(\text{FN})$	72.64
ΔLF	7.13

According to the Variance Inflation Factor (VIF) test results, the variables log_ASK_diff, log_RPK_diff, log_PAX_diff, and log_FN_diff exhibited very high VIF values ($VIF > 10$), indicating the presence of multicollinearity among these variables. Only the LF_diff variable had an acceptable VIF value of 7.13. Therefore, it was decided to employ the Panel-Ridge Regression model (Hsiao, 2003).

Table 5.5. Testing the Presence of Heteroskedasticity and Serial Autocorrelation

Test	Test Statistics	Degree of Freedom	p-value	Result
Breusch-Godfrey	0.78958	1	0.3742	No autocorrelation
Breusch-Pagan	26.233	5	<0.001	Heteroskedasticity was detected

According to the Breusch-Godfrey test results, no autocorrelation was detected in the fixed effects model ($p = 0.3742$). However, the Breusch-Pagan test indicated the presence of heteroskedasticity in the model ($p < 0.001$). Since heteroskedasticity can lead to misleading standard errors, robust standard errors were applied to ensure the reliability of the model results.

The Hausman test could not be performed for the Swamy-Arora random-effects model, as the number of observations (3) was insufficient relative to the total number of variables (6). Therefore, the analysis was directly conducted using the fixed-effects model (Güngör & Kaygın, 2015).

Table 5.6. Balanced Panel Model Analysis Using the Fixed-Effects Model

	β	SE	t-value	p-value
$\Delta \log(\text{ASK})$	0.239	0.224	1.068	0.287
$\Delta \log(\text{RPK})$	-0.168	0.208	-0.807	0.421
$\Delta \log(\text{PAX})$	0.020	0.157	0.127	0.899
$\Delta \log(\text{FN})$	-0.077	0.168	-0.460	0.646
ΔLF	0.875	0.346	2.525	0.012
Dummy _{pandemic}	-0.017	0.018	-0.990	0.324
$R^2=0.112$; Adjusted $R^2=0.0750$; Model $F=4.077$; Model $p=0.0007$				
	β	Robust SE	t-value	p-value
$\Delta \log(\text{ASK})$	0.239	0.244	0.982	0.327
$\Delta \log(\text{RPK})$	-0.168	0.140	-1.196	0.233
$\Delta \log(\text{PAX})$	0.020	0.092	0.216	0.829
$\Delta \log(\text{FN})$	-0.077	0.212	-0.366	0.715
ΔLF	0.875	0.378	2.312	0.022*
Dummy _{pandemic}	-0.017	0.014	-1.222	0.223
Ridge Model: <i>Optimum Ridge penalized value (λ): 6.095296e-15</i> $\beta_{(\text{Intercept})} = -6.505213e-18$ $\beta_{\Delta \log(\text{ASK})} = 0$ $\beta_{\Delta \log(\text{RPK})} = -5.056582e-18$ $\beta_{\Delta \log(\text{PAX})} = -3.375936e-18$ $\beta_{\Delta \log(\text{FN})} = 2.237910e-17$ $\beta_{\Delta \text{LF}} = 7.971090e-17$ $\beta_{\text{pandemic}} = -1.287199e-17$				

*:p<0,05

The results presented in Table 5.6 were obtained through balanced panel data analysis using the fixed-effects model. The logarithmic change in stock prices ($\Delta \log(\text{SP})$) was used as the dependent variable, while independent variables included the logarithmic changes in available seat kilometers ($\Delta \log(\text{ASK})$), revenue passenger kilometers ($\Delta \log(\text{RPK})$), number of passengers ($\Delta \log(\text{PAX})$), number of flights ($\Delta \log(\text{FN})$), and changes in load factor (ΔLF). The overall explanatory power of the model was calculated as $R^2 = 0.112$, with an adjusted $R^2 = 0.0750$. The model was statistically

significant ($F = 4.077$, $p < 0.001$), indicating that the independent variables collectively had a significant effect on the dependent variable (Weisz, 2016).

Based on standard error (SE) estimations, the load factor (ΔLF) exhibited a positive ($Beta = 0.875$) and significant ($p = 0.012$) effect on stock prices. The coefficients of other independent variables ($\Delta \log(ASK)$, $\Delta \log(RPK)$, $\Delta \log(PAX)$, $\Delta \log(FN)$, $DummyPandemic$) were not statistically significant ($p > 0.05$). Robust standard errors were applied to mitigate the effects of heteroskedasticity, and analysis with robust standard errors continued to show a significant positive impact of load factor ($Beta = 0.874$, $p = 0.022$), while the other variables remained statistically insignificant.

The model was also examined using Ridge penalization, and the optimal Ridge penalization value was calculated as $\lambda = 6.095296 \times 10^{15}$. Ridge penalization was applied to mitigate multicollinearity among independent variables; however, none of the variables, except load factor, were found to be statistically significant (B. H. Baltagi, 2013). Furthermore, under Ridge penalization, the penalization term specifically reduced the coefficient of the $\Delta \log(ASK)$ variable to zero ($Beta = 0$), indicating that this variable does not play a meaningful role in explaining stock price changes within the model. According to these findings, the model under Ridge penalization also confirms that the load factor has a robust and positive impact on stock prices. The model equations are as follows:

$$\Delta \log(SP) = 0.239 * \Delta \log(ASK) - 0.168 * \Delta \log(RPK) + 0.020 * \Delta \log(PAX) - 0.077 * \Delta \log(FN) + 0.875 * \Delta LF - 0.017 * Dummy_{Pandemic}$$

$$\begin{aligned} \Delta \log(SP) = & -6.505213 \times 10^{-18} - 5.065823 \times 10^{-18} * \Delta \log(ASK) \\ & - 3.375936 \times 10^{-18} * \Delta \log(RPK) + 1.580089 \times 10^{-18} \\ & * \Delta \log(PAX) + 2.237910 \times 10^{-18} * \Delta \log(FN) \\ & + 8.350639 \times 10^{-17} * \Delta LF - 1.287199 \times 10^{-17} \\ & * Dummy_{Pandemic} \end{aligned}$$

Due to the high level of multicollinearity observed in the dynamic panel model, the independent variables were analyzed separately (Güriş, 2015). A total of six models were established and presented in Table 5.7.

Table 5.7. Dynamic Panel Model

Model 1	β	SE	z-value	p-value
lag(log_SP, 1)	0.8775	0.01928	45.4985	<2e-16 ***
$\Delta\log(\text{ASK})$	0.0007	0.0125	0.0592	0.9528
Sargan test: chisq(66) = 3 (p-value = 1)				
Autocorrelation test (1): normal = -1.567918 (p-value = 0.1169)				
Autocorrelation test (2): normal = -1.161001 (p-value = 0.24564)				
Wald test for coefficients: chisq(2) = 777626.8 (p-value = < 2.22e-16)				
Model 2	β	SE	z-value	p-value
lag(log_SP, 1)	0.8576	0.01754	48.8961	<2e-16 ***
$\Delta\log(\text{RPK})$	0.0116	0.01006	1.1508	0.2498
Sargan Test chisq(66) = 3 (p-value = 1)				
Autocorrelation Test (1) normal = -1.558392 (p-value = 0.11914)				
Autocorrelation Test (2) normal = -0.6767111 (p-value = 0.49859)				
Wald Test for Coefficients chisq(2) = 442170469 (p-value = < 2.22e-16)				
Model 3	β	SE	z-value	p-value
lag(log_SP, 1)	0.8173	0.02815	29.0317	<2e-16 ***
$\Delta\log(\text{LF})$	0.1407	0.07300	1.9272	0.05396
Sargan Test chisq(66) = 3 (p-value = 1)				
Autocorrelation Test (1) normal = -1.530171 (p-value = 0.12597)				
Autocorrelation Test (2) normal = 0.8302124 (p-value = 0.40642)				
Wald Test for Coefficients chisq(2) = 180530.7 (p-value = < 2.22e-16)				
Model 5	β	SE	z-value	p-value
lag(log_SP, 1)	0.8604	0.01655	51.991	<2e-16 ***
$\Delta\log(\text{PAX})$	0.0113	0.01085	1.042	0.2974
Sargan Test chisq(66) = 3 (p-value = 1)				
Autocorrelation Test (1) normal = -1.554773 (p-value = 0.12)				
Autocorrelation Test (2) normal = -0.6329556 (p-value = 0.52676)				
Wald Test for Coefficients chisq(2) = 6090141 (p-value = < 2.22e-16)				
Model 6	β	SE	z-value	p-value
lag(log_SP, 1)	0.8856	0.01457	60.7673	<2e-16 ***
$\Delta\log(\text{FN})$	-0.0053	0.00933	-0.5706	0.5683
Sargan Test chisq(66) = 3 (p-value = 1)				
Autocorrelation Test (1) normal = -1.567922 (p-value = 0.1169)				
Autocorrelation Test (2) normal = -1.103166 (p-value = 0.26996)				
Wald Test for Coefficients chisq(2) = 258905.2 (p-value = < 2.22e-16)				

The dynamic panel models presented in Table 5.7 show that the lagged value of stock prices (SP) is highly significant in all models ($p < 2e-16$), indicating a strong autoregressive dependence in stock prices. Among independent variables, the Load Factor (LF) is significant at the 90% confidence level ($p = 0.05396$) and has a positive effect on stock prices. However, the variables ASK, RPK, PAX, and FN were found to be statistically insignificant ($p > 0.1$), indicating no clear impact on stock prices. The results of the Sargan test ($p = 1$) confirmed that the models are valid regarding the over-identifying restrictions, while autocorrelation tests indicated no second-order autocorrelation (AR(2)). Moreover, the Wald tests demonstrated that the models are robustly specified overall ($p < 2.22e-16$). Consequently, LF (load factor) appears as the most critical variable influencing stock prices, whereas other operational performance indicators do not display significant effects (Güngör & Kaygın, 2015).

5.10.1. Time Series Analysis

In this section, separate time-series analyses were conducted individually for the three companies using Ridge regression and ARDL models. Initially, decomposition analysis was performed to identify seasonality, trends, and random walk characteristics in the data (Ayaydın & Dağlı, 2012).

Decomposition of multiplicative time series

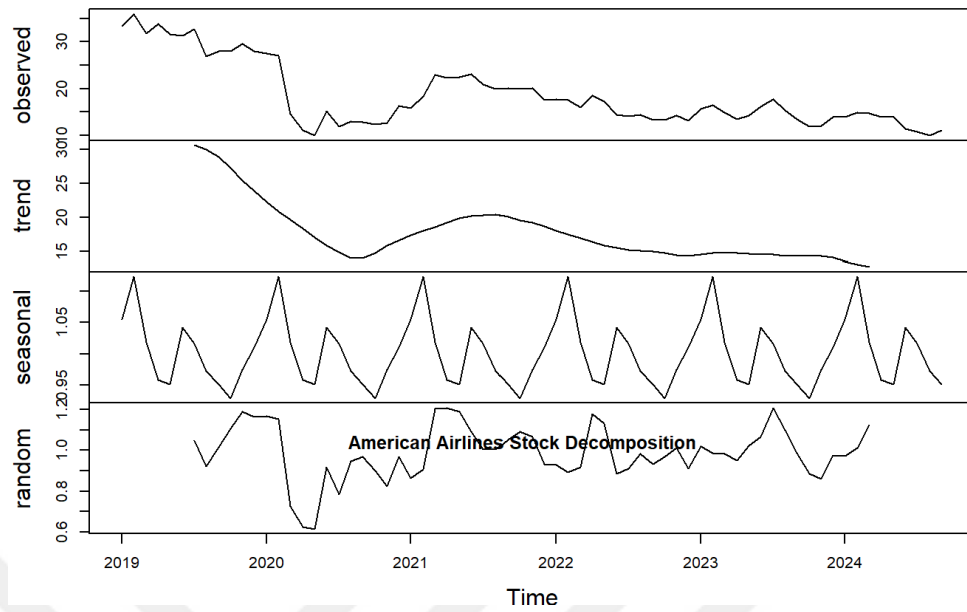


Figure 5.8. Decomposition Analysis of American Airlines

Decomposition of multiplicative time series

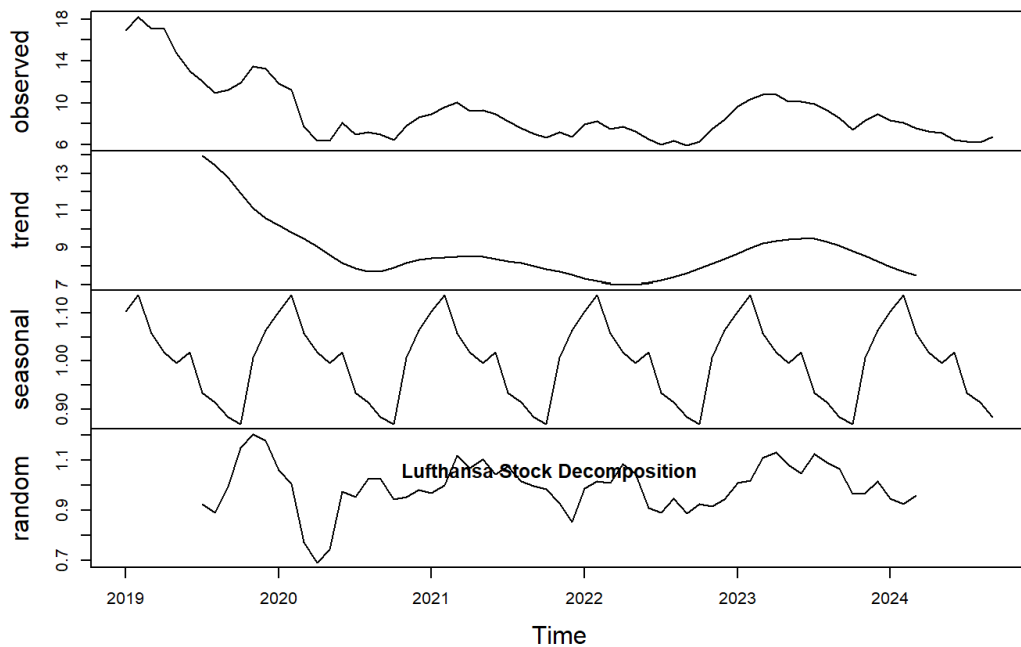


Figure 5.9. Decomposition Analysis of Lufthansa

Decomposition of multiplicative time series

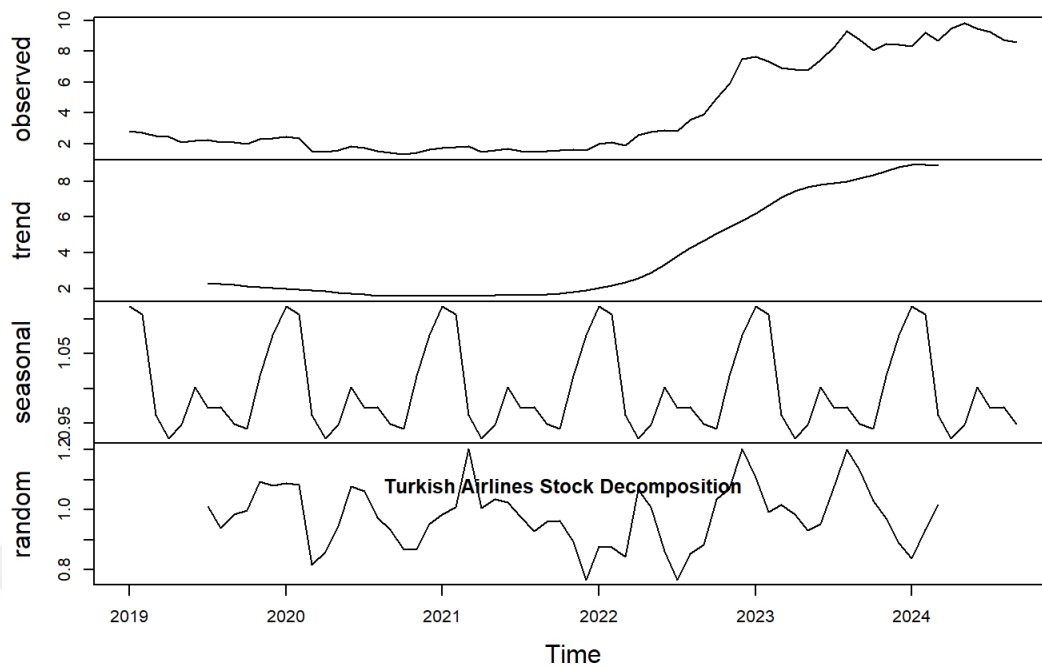


Figure 5.10. Decomposition Analysis of Turkish Airlines

- American Airlines:** In the observed series, there is a notable decline in early 2020, followed by a limited recovery. The trend component reaches its lowest point around mid-2020 and gradually rises afterward, demonstrating a relatively horizontal pattern during the 2022–2023 period. The seasonal component displays regular fluctuations of similar magnitudes, while the random component exhibits moderate fluctuations without any distinct directional trend.
- Lufthansa:** The observed series experienced a sharp decline from late 2019 until mid-2020, followed by a partial recovery during the 2021–2022 period. Approaching 2024, the series moves into a more stationary trajectory. The trend component initially declines throughout 2020, rises around 2022, and subsequently stabilizes horizontally. The seasonal component demonstrates clearly recurring periodic fluctuations. The random component fluctuates within a limited range, showing no extreme spikes.
- Turkish Airlines:** The observed series follows a relatively stable pattern between 2019 and 2020; however, it displays a notable upward trend starting from late 2021, with values in 2024 remaining at higher levels compared to previous periods. Initially flat or slightly downward, the trend component rises

significantly due to a strong upward movement after late 2022. The seasonal component has periodic fluctuations with similar magnitudes. Meanwhile, the random component remains limited, characterized by moderate fluctuations independent of trend and seasonality.

5.10.1.1. American Airlines Time Series Analysis

The stationarity of the variables for American Airlines was tested using the Augmented Dickey-Fuller (ADF) test (Yerdelen Tatoğlu, 2018). The results are presented in Table 5.8.

Table 5.8. American Airlines Stationery Tests

Variable	ADF p-value	Stationary Situation
log(ASK)	0.2692	Not Stationary
$\Delta(\log(\text{ASK}))$	0.0542	Borderline Stationary
log(RPK)	0.2166	Not Stationary
$\Delta(\log(\text{RPK}))$	0.0100	Stationary
log(PAX)	0.1306	Not Stationary
$\Delta(\log(\text{PAX}))$	0.0100	Stationary
log(FN)	0.2341	Not Stationary
$\Delta(\log(\text{FN}))$	0.0403	Stationary
log(SP)	0.2741	Not Stationary
$\Delta(\log(\text{SP}))$	0.0168	Stationary
LF	0.0526	Borderline Stationary
$\Delta(\text{LF})$	0.0100	Stationary

According to the stationarity test results (ADF test) presented in Table 5.8, the variables $\log(\text{ASK})$, $\log(\text{RPK})$, $\log(\text{PAX})$, $\log(\text{FN})$, and $\log(\text{SP})$ were found to be non-stationary ($p > 0.05$). However, when the first differences (Δ) of these variables were taken, the ADF test results became statistically significant ($p < 0.05$), indicating that the differenced variables are stationary. The LF variable was found to be borderline stationary ($p = 0.0526$), but became stationary after taking its first difference (ΔLF). These findings indicate that the first differences of non-stationary variables should be used in the modeling process to satisfy the stationarity assumption.

The Breusch-Godfrey test result yielded a p-value of 0.003355, which leads to the rejection of the null hypothesis at the 5% significance level. This indicates the presence of first-order autocorrelation in the model. Since the presence of autocorrelation can compromise the reliability of model estimations, it was determined that either HAC (Newey-West) standard errors should be applied or alternative modeling techniques, such as ARDL, which can address autocorrelation, should be considered (Sevüktekin & Nargeleşkenler, 2010).

According to the VIF test results conducted within the scope of multicollinearity analysis, the variables $\Delta(\log(\text{RPK}))$ (249.90), $\Delta(\log(\text{PAX}))$ (642.38), $\Delta(\log(\text{FN}))$ (175.32), and $\Delta(\log(\text{LF}))$ (334.05) exhibited extremely high VIF values. This indicates strong linear relationships among the independent variables. The variable $\Delta(\log(\text{ASK}))$ was found to cause perfect collinearity and was therefore excluded from the model, as its logarithmic transformation further increased multicollinearity. However, since the remaining VIF values remained at high levels, it was decided to apply the Ridge regression method to control for multicollinearity and enhance the reliability of the model estimations (Kiracı, 2017).

According to the results of the Breusch-Pagan heteroskedasticity test, the test statistic was calculated as 6.9904 and the p-value as 0.1364. Since the significance level exceeds 0.05, this suggests that heteroskedasticity is not statistically significant in the model. Accordingly, it provides evidence that the error terms have constant variance.

After confirming the absence of heteroskedasticity, the Bai-Perron multiple structural break test identified two significant breakpoints within the model. The first breakpoint occurred at the 17th observation, corresponding to May 2020. The second breakpoint

was identified at the 27th observation, aligning with March 2021. These structural breaks indicate substantial changes in the determinants of stock prices during these periods. The breaks can be associated with the impact of the COVID-19 pandemic on the aviation sector and the following recovery process.

Finally, the Jarque-Bera test was used to examine the normality assumption of the model's residuals. The test yielded a statistic of 8.7042 with a p-value of 0.01288. Since the p-value is below 0.05, it indicates that the residuals do not follow a normal distribution. Consequently, it was decided to employ HAC (Newey-West) standard errors to enhance the reliability of the model's standard errors. However, following the integration of both HAC and Ridge regression, cross-validation results revealed an overfitting issue. As a result, Ridge regression was excluded from the model, and instead, lagged terms were combined to address autocorrelation (Sevüktekin & Nargeleçekenler, 2010).

Table 5.9. Ridge Regression Model Estimation Results for American Airlines

Variable	Beta	Std. Error	Std. Beta	t-value	p
$\Delta(\log(\text{RPK}))$	0,0114	0,0113	0,0303	10,072	0,3180
$\Delta(\log(\text{PAX}))$	0,0120	0,0118	0,0303	10,212	0,3114
$\Delta(\log(\text{FN}))$	0,0126	0,0202	0,0151	0,6210	0,5370
$\Delta(\log(\text{LF}))$	0,0202	0,0243	0,0331	0,8332	0,4082
DummyCOVID19	0,0087	0,0068	0,0229	12,907	0,2019
$L_1_ \Delta(\log(\text{RPK}))$	0,0077	0,0082	0,0204	0,9344	0,3540
$L_1_ \Delta(\log(\text{PAX}))$	0,0078	0,0081	0,0197	0,9633	0,3394
$L_1_ \Delta(\log(\text{FN}))$	0,0045	0,0151	0,0054	0,2972	0,7674
$L_1_ \Delta(\log(\text{LF}))$	0,0158	0,0165	0,0258	0,9547	0,3437

F: 0,653; Adjusted R²: -0,0495

According to the results of the Ridge regression model, the explanatory power of the independent variables on stock price changes was found to be low (Adjusted $R^2 = -0.0495$). None of the coefficients were statistically significant, with the lowest p-value belonging to the DummyCOVID19 variable ($p = 0.2019$). Among the independent variables, the highest standardized beta coefficient was observed for $\Delta(\log(LF))$ (0.0331), while the lagged variables ($L1_ \Delta$) did not exhibit any notable effect in the model. The F-statistic was calculated as 0.653, indicating that the model is not statistically significant overall. These findings suggest that while Ridge regression helps mitigate multicollinearity, it does not render the independent variables statistically significant in explaining stock price movements (Karagöz, 2016).

Table 5.10. ARDL Model Estimation Results for American Airlines

Variable	Beta	Std. Error	t-value	p-value
Coefficient (Intercept)	0.000	4,17E-15	0.000	1.000
$L(\Delta(\log(SP)), p_best)$	1.000	3,08E-14	3,25E+19	<2e-16 ***
$L(\Delta(\log(RPK)), q_best)$	1,17E-13	1,69E-13	0.692	0.492
$L(\Delta(\log(PAX)), q_best)$	1,86E-14	3,15E-13	0.059	0.953
$L(\Delta(\log(FN)), q_best)$	-1,55E-13	3,56E-13	-0.435	0.665
$L(\Delta(\log(LF)), q_best)$	-1,41E-13	3,59E-13	-0.391	0.697
DummyCOVID19	-8,44E-15	1,21E-14	-0.698	0.488

RSS: 3.053e-17; F: 0,653; Adjusted R^2 : 1; F: 2.226e+32; $p = <2.2e-16$

According to the ARDL model estimation results, the lagged value ($L(\Delta(\log(SP)), p_best)$) of the dependent variable ($\Delta(\log(SP))$) was found to be statistically significant ($p < 2e-16$), with its coefficient estimated as 1. For all other independent variables, p-values exceeded 0.05, indicating that they were not statistically significant. The R^2 and adjusted R^2 values of the model were both calculated as 1, suggesting that the model explains the entire variation in the dependent variable. However, such excessively high values may indicate that the model suffers from overfitting. The F-statistic was extremely large (2.226e+32), and the model was found to be statistically significant overall ($p < 2.2e-16$). Nevertheless, the model was accepted as the optimal

specification based on the Akaike Information Criterion (AIC) used for selecting lag length (Contuk & Güngör, 2016).

Table 5.11. UECM Model Estimation Results for American Airlines

Variable	Beta	Std. Error	t-value	p-value
Coefficient (Intercept)	0.000e+00	2,11E-30	0.000e+00	1.000
$L(\Delta(\log(SP)), p_best)$	1,00E+03	1,56E-29	6,43E+34	<2e-16 ***
$L(\Delta(\log(RPK)), q_best)$	1,17E-13	8,52E-29	1,37E+18	<2e-16 ***
$L(\Delta(\log(PAX)), q_best)$	1,86E-14	1,59E-28	1,17E+17	<2e-16 ***
$L(\Delta(\log(FN)), q_best)$	-1,55E-13	1,80E-28	-8,60E+17	<2e-16 ***
$L(\Delta(\log(LF)), q_best)$	-1,41E-13	1,81E-28	-7,74E+17	<2e-16 ***
DummyCOVID19	-8,44E-15	6,12E-30	-1,38E+18	<2e-16 ***
Error Term (ECT)	1,00E+03	6,53E-14	1,53E+19	<2e-16 ***

According to the UECM model estimation results, the lagged value of the dependent variable ($L(\Delta(\log(SP)), p_best)$) and all lagged values of the independent variables ($L(\Delta(\log(RPK)), q_best)$, $L(\Delta(\log(PAX)), q_best)$, $L(\Delta(\log(FN)), q_best)$, $L(\Delta(\log(LF)), q_best)$) were found to be statistically significant ($p < 2e-16$). However, the magnitude of the coefficients and the scale of the residuals suggest that the model may suffer from overfitting. The error correction term (ECT) was calculated as 1000, which is exceptionally high and indicates an unrealistically rapid speed of adjustment toward equilibrium. This raises concerns about whether the model reliably captures the long-run relationship. The excessive significance of all coefficients and the extremely small residuals point to a possible structural modeling error or over-parameterization.

Table 5.12. RECM Estimation Results for American Airlines

Variable	Beta (Coefficient)	Std. Error	t-value	p-value
Coefficient (Intercept)	-0,01903	0,01731	-1,099	0,2761
$\Delta(\log(\text{RPK}))$	1,036	0,6948	1,491	0,1411
$\Delta(\log(\text{PAX}))$	2,290	1,289	1,776	0,0807
$\Delta(\log(\text{FN}))$	-3,328	1,433	-2,322	0,0236 *
$\Delta(\log(\text{LF}))$	-3,245	1,447	-2,242	0,0287 *
DummyCOVID19	0,001506	0,05079	0,030	0,9764
Error Correction Term (ECT)	-12,210	5,42E+17	0,000	1,000

Adjusted R²: 0.1287; F-statistics: 2.625; Model p-value: 0.02509; *: p<0,05

According to the RECM model estimation results, the model exhibited low explanatory power in capturing the short-term dynamics of stock price movements (Adjusted R² = 0.1287). The F-statistic was calculated as 2.625, and the overall significance of the model was found to be marginally acceptable at the 5% significance level (p = 0.02509). Regarding short-term coefficients, the number of flights ($\Delta(\log(\text{FN}))$) and the load factor ($\Delta(\log(\text{LF}))$) were found to be negative and statistically significant (p < 0.05). The number of passengers ($\Delta(\log(\text{PAX}))$) was borderline significant at the 10% level (p = 0.0807), suggesting that passenger numbers positively influence stock prices in the short run. The remaining variables were not statistically significant (p > 0.05). The error correction term (ECT) was estimated as -12.210; however, it was found to be statistically insignificant (p = 1.000), indicating that a return to long-run equilibrium is not supported by the model (Tari, 2015).

5.10.1.2. Lufthansa Time Series Analysis

The stationarity of the variables for Lufthansa was tested using the Augmented Dickey-Fuller (ADF) test (Yerdelen Tatoğlu, 2018). The results are presented below.

Table 5.13. Lufthansa Stationery Test

Variable	ADF p-value	Stationary Situation
log(ASK)	0.2692	Not Stationary
$\Delta(\log(\text{ASK}))$	0.0542	Borderline Stationary
log(RPK)	0.2166	Not Stationary
$\Delta(\log(\text{RPK}))$	0.0100	Stationary
log(PAX)	0.1306	Not Stationary
$\Delta(\log(\text{PAX}))$	0.0100	Stationary
log(FN)	0.2341	Not Stationary
$\Delta(\log(\text{FN}))$	0.0403	Stationary
log(SP)	0.2741	Not Stationary
$\Delta(\log(\text{SP}))$	0.0168	Stationary
LF	0.0526	Borderline Stationary
$\Delta(\text{LF})$	0.0100	Stationary

According to the stationarity test results (ADF test) presented in Table 5.13, the variables log(ASK), log(RPK), log(PAX), log(FN), log(SP), and log(LF) were found to be non-stationary ($p > 0.05$). However, when the first differences (Δ) of these variables were taken, the ADF test results became statistically significant ($p < 0.05$), indicating that the differenced variables are stationary. The LF variable was found to be borderline stationary ($p = 0.0517$), but became stationary after taking its first difference (ΔLF). These results suggest that first-differenced versions of non-stationary variables should be used in the modeling process to satisfy the stationarity assumption.

According to the Breusch-Godfrey test, the p-value was 0.1744, and therefore the null hypothesis could not be rejected at the 5% significance level. This indicates the absence of autocorrelation in the model. The lack of autocorrelation improves the reliability of model estimations and suggests that no additional correction methods are necessary (Sevüktekin & Nargeleçekenler, 2010).

Based on the VIF test results conducted as part of the multicollinearity analysis, the variables $\Delta(\log(\text{RPK}))$ (20.91), $\Delta(\log(\text{PAX}))$ (34.35), $\Delta(\log(\text{FN}))$ (35.99), and

$\Delta(\log(LF))$ (3.73) exhibited high VIF values. This indicates strong linear relationships among the independent variables. The variable $\Delta(\log(ASK))$, which was found to cause perfect collinearity and whose logarithmic transformation further intensified multicollinearity, was removed from the model. However, since certain variables still presented high VIF values, it was decided to apply the Ridge regression method in order to mitigate multicollinearity and enhance the reliability of the model estimations (Kiracı, 2017).

According to the Breusch-Pagan heteroskedasticity test results, the test statistic was calculated as 8.1161 and the p-value as 0.08742. Since the significance level exceeds 0.05, this suggests that heteroskedasticity is not statistically significant in the model. This result indicates that the error terms likely have constant variance. However, the fact that the p-value is close to the 0.10 level may imply the presence of mild heteroskedasticity. Nevertheless, at the 5% significance level, heteroskedasticity is not considered a problem.

After confirming the absence of heteroskedasticity, the Bai-Perron multiple structural break test identified two significant breakpoints within the model. The first breakpoint occurred at the 17th observation, corresponding to May 2020, while the second was at the 27th observation, corresponding to April 2021. These findings suggest significant changes in the determinants of stock prices during the May 2020–April 2021 period. Accordingly, a DummyCOVID19 variable was created to represent this period and included in the model. The coefficient for DummyCOVID19 was estimated as 0.05224; however, it was not statistically significant ($p = 0.1306$). The model exhibited low explanatory power, with an adjusted R^2 of 0.04686. The F-statistic was 1.659, and the overall significance of the model was found to be statistically insignificant ($p = 0.158$).

Finally, the Jarque-Bera test was used to assess the normality assumption of the residuals. The test yielded a statistic of 2.36 and a p-value of 0.3073. Since the p-value is greater than 0.05, it confirms that the residuals satisfy the normality assumption. Therefore, no additional correction was deemed necessary with regard to the reliability of standard errors (Sevüktekin & Nargeleçekenler, 2010).

Table 5.14. Ridge Regression Model Estimation Results for Lufthansa

Variable	Beta	Std. Error	Std. Beta	t-value	p
$\Delta(\log(\text{RPK}))$	0,0142	0,0166	0,0574	0,8594	0,3935
$\Delta(\log(\text{PAX}))$	0,0087	0,0152	0,0376	0,5715	0,5697
$\Delta(\log(\text{FN}))$	0,0065	0,0209	0,0218	0,3122	0,7560
$\Delta(\log(\text{LF}))$	0,0567	0,0667	0,0489	0,8509	0,3981
DummyCOVID19	0,0275	0,0145	0,1032	19,012	0,0619

F: 1,1135; Adjusted R²: 0,0085

According to the results of the Ridge regression model, the explanatory power of the independent variables on stock price changes was found to be low (Adjusted R² = 0.0085), and the model was not statistically significant overall (F-statistic = 1.1135, $p > 0.05$). None of the coefficients were statistically significant, with the lowest p-value observed for the DummyCOVID19 variable ($p = 0.0619$), which does not meet the 5% significance threshold but may be considered marginally significant. Among the independent variables, the highest standardized beta coefficient was observed for $\Delta(\log(\text{RPK}))$ (0.0574), while the effects of $\Delta(\log(\text{FN}))$ and $\Delta(\log(\text{PAX}))$ were found to be relatively weak. Although the Ridge regression method effectively reduced multicollinearity, it did not render the effects of the independent variables on stock prices statistically significant (Karagöz, 2016).

Table 5.15. ARDL Model Estimation Results for Lufthansa

Variable	Beta	Std. Error	t-value	p-value
Coefficient (Intercept)	3,39E-15	6,45E-16	5.259	2.03e-06 **
$L(\Delta(\log(\text{SP})), p_best)$	1.000	6,15E-15	1,63E+20	<2e-16 ***
$L(\Delta(\log(\text{RPK})), q_best)$	3,68E-16	6,73E-15	0.055	0.957
$L(\Delta(\log(\text{PAX})), q_best)$	2,07E-15	8,05E-15	0.257	0.798
$L(\Delta(\log(\text{FN})), q_best)$	-1,37E-15	1,09E-14	-0.126	0.900
$L(\Delta(\log(\text{LF})), q_best)$	-2,67E-15	1,35E-14	-0.198	0.844
DummyCOVID19	-7,41E-16	1,67E-15	-0.443	0.659

RSS: 4.65e-18; F: 0,653; Adjusted R²: 1; F: 5.038e+33; $p = <2.2\text{e-}16$

According to the ARDL model estimation results, the lagged value of the dependent variable ($\Delta(\log(\text{SP}))$) was found to be statistically significant ($p < 2e-16$), with its coefficient estimated as 1. However, all other independent variables had p-values exceeding 0.05 and were not statistically significant. The R^2 and adjusted R^2 values of 1 suggest that the model explains the entire variation in the dependent variable; however, such values raise concerns about potential overfitting. Although the F-statistic was extremely high ($5.038e+33$), and the model was found to be statistically significant overall ($p < 2.2e-16$), the lack of significance among the independent variables raises doubts about the model's reliability. Nevertheless, the model was accepted based on the lag length selected according to the Akaike Information Criterion (AIC) (Contuk & Güngör, 2016).

Table 5.16. UECM Model Estimation Results for Lufthansa

Variable	Beta	Std. Error	t-value	p-value
Coefficient (Intercept)	3,39E-15	2,08E-31	1,63E+19	<2e-16 ***
$L(\Delta(\log(\text{SP})), p_best)$	1.000	1,98E-30	5,05E+35	<2e-16 ***
$L(\Delta(\log(\text{RPK})), q_best)$	3,68E-16	2,17E-30	1,70E+17	<2e-16 ***
$L(\Delta(\log(\text{PAX})), q_best)$	2,07E-15	2,59E-30	7,98E+17	<2e-16 ***
$L(\Delta(\log(\text{FN})), q_best)$	-1,37E-15	3,49E-30	-3,92E+17	<2e-16 ***
$L(\Delta(\log(\text{LF})), q_best)$	-2,67E-15	4,33E-30	-6,15E+17	<2e-16 ***
DummyCOVID19	-7,41E-16	5,37E-31	-1,38E+18	<2e-16 ***
Error Term (ECT)	1.000	4,15E-14	2,41E+19	<2e-16 ***

RSS: 1.496e-33; F: 0,653; Adjusted R^2 : 1; F: 5 4.17e+64; $p < 2.2e-16$

According to the UECM model estimation results, the lagged value of the dependent variable ($L(\Delta(\log(\text{SP})), p_best)$) and all lagged values of the independent variables ($L(\Delta(\log(\text{RPK})), q_best)$, $L(\Delta(\log(\text{PAX})), q_best)$, $L(\Delta(\log(\text{FN})), q_best)$, $L(\Delta(\log(\text{LF})), q_best)$) were found to be statistically significant ($p < 2e-16$). However, the magnitude of the coefficients and the scale of the residuals suggest that the model may be overfitted. The error correction term (ECT) was estimated as 1, which is exceptionally high and implies an unrealistically rapid adjustment to long-run

equilibrium. This raises concerns about the model's ability to reliably represent long-run dynamics. The excessive significance of all coefficients and the extremely small residuals point to a possible structural misspecification or overparameterization.

Table 5.17. RECM Estimation Results for Lufthansa

Variable	Beta	Std. Error	t-value	p-value
Coefficient (Intercept)	-2,440e-02	1,316e-02	-1,854	0,0686
$\Delta(\log(\text{RPK}))$	1,788e-01	1,393e-01	1,283	0,2043
$\Delta(\log(\text{PAX}))$	3,108e-02	1,688e-01	0,184	0,8546
$\Delta(\log(\text{FN}))$	-1,963e-01	2,264e-01	-0,867	0,3895
$\Delta(\log(\text{LF}))$	-2,940e-02	2,826e-01	-0,104	0,9175
DummyCOVID19	5,416e-02	3,434e-02	1,577	0,1201
Error Correction Term (ECT)	-1,541e+00	2,709e+15	0,000	1,000

Adjusted R²: 0.03837; F-statistics: 1.439; Model p-value: 0.215

According to the RECM model estimation results, the explanatory power of the model in capturing the short-term dynamics of stock price movements was found to be low (Adjusted R² = 0.03837). The F-statistic was calculated as 1.439, and the overall significance of the model was not statistically acceptable (p = 0.215). An examination of the short-term coefficients revealed that none of the variables were statistically significant (p > 0.05). Although the DummyCOVID19 variable had the lowest p-value, it did not meet the threshold for statistical significance, even at the 12% level. The error correction term (ECT) was estimated as -1.541; however, it was not statistically significant (p = 1.000). Overall, the model demonstrated poor fit, suggesting that the short-term variables do not have a clear impact on stock prices (Tari, 2015).

5.10.1.3. Turkish Airlines Time Series Analysis

The stationarity of the variables for Turkish Airlines was tested using the Augmented Dickey-Fuller (ADF) test (Yerdelen Tatoğlu, 2018). The results are presented below.

Table 5.18. Stationarity Tests for Turkish Airlines

Variable	ADF p-value	Stationary Situation
log(ASK)	0.0100	Stationary
$\Delta(\log(\text{ASK}))$	0.0100	Stationary
log(RPK)	0.0153	Stationary
$\Delta(\log(\text{RPK}))$	0.0100	Stationary
log(PAX)	0.0100	Stationary
$\Delta(\log(\text{PAX}))$	0.0100	Stationary
log(FN)	0.0100	Stationary
$\Delta(\log(\text{FN}))$	0.0100	Stationary
log(SP)	0.5320	Not Stationary
$\Delta(\log(\text{SP}))$	0.1059	Borderline Stationary
LF	0.4724	Not Stationary
$\Delta(\text{LF})$	0.0209	Stationary

According to the stationarity test results (ADF test) presented in Table 5.18, the variables log(SP) and log(LF) were found to be non-stationary ($p > 0.05$). However, the variables log(ASK), log(RPK), log(PAX), and log(FN) were already stationary at the level. When the first differences (Δ) of the non-stationary variables were taken, $\Delta(\log(\text{LF}))$ became stationary ($p < 0.05$), while $\Delta(\log(\text{SP}))$ was identified as borderline stationary ($p = 0.1059$). These results suggest that first differences of non-stationary variables should be used in the modeling process, whereas log(ASK), log(RPK), log(PAX), and log(FN) can be directly included in the model.

According to the Breusch-Godfrey test, the p-value was 0.2862, meaning that the null hypothesis could not be rejected at the 5% significance level. This indicates the absence of autocorrelation in the model. The lack of autocorrelation improves the reliability of the model estimates and shows that no additional correction techniques are required (Sevüktekin & Nargeleçekenler, 2010).

As part of the multicollinearity analysis, VIF test results revealed high values for the variables $\Delta(\log(\text{RPK}))$ (63.84), $\Delta(\log(\text{PAX}))$ (560.22), $\Delta(\log(\text{FN}))$ (413.68), and $\Delta(\log(\text{LF}))$ (8.82), indicating strong linear relationships among the independent

variables. The variable $\Delta(\log(\text{ASK}))$ was identified as causing perfect collinearity and was therefore removed from the model, as its logarithmic transformation further intensified multicollinearity. However, given that some variables still exhibited high VIF values, it was decided to apply Ridge regression in order to control multicollinearity and improve the reliability of model estimates (Kiracı, 2017).

According to the Breusch-Pagan heteroskedasticity test results, the test statistic was calculated as 11.46 and the p-value as 0.02185. Since the p-value is below 0.05, heteroskedasticity is considered statistically significant in the model. This indicates that the error terms do not have constant variance and that the model suffers from a heteroskedasticity problem. Therefore, the application of robust standard errors or alternative modeling techniques may be necessary to enhance the reliability of model estimations.

Following the detection of heteroskedasticity, the Bai-Perron multiple structural break test identified two significant breakpoints within the model. The first occurred at the 17th observation, corresponding to May 2020, and the second at the 35th observation, corresponding to November 2021. These findings indicate that significant changes in the determinants of stock prices occurred during the May 2020–November 2021 period. Accordingly, a DummyCOVID19 variable was created to represent this period and included in the model. The coefficient of DummyCOVID19 was estimated as -0.02205; however, it was not found to be statistically significant ($p = 0.4846$). The explanatory power of the model was low, with an adjusted R^2 of 0.0571. The F-statistic was calculated as 1.812, and the overall model significance level was $p = 0.1237$, indicating that the model was not statistically significant overall.

Finally, the Jarque-Bera test was used to assess whether the model's residuals follow a normal distribution. The test yielded a statistic of 4.747 and a p-value of 0.09315. As the p-value is greater than 0.05, the residuals largely satisfy the normality assumption. However, since the p-value is close to the 0.10 level, there may be a mild deviation from normality. Nevertheless, it was concluded that no additional corrections are required in terms of the reliability of the standard errors (Sevüktekin & Nargeleçekenler, 2010).

Table 5.19. Ridge Regression Model Estimation Results for Turkish Airlines

Variable	Beta	Std. Error	Std. Beta	t-value	p
$\Delta(\log(\text{RPK}))$	0,0016	0,0055	0,0084	0,3020	0,7637
$\Delta(\log(\text{PAX}))$	0,0018	0,0048	0,0096	0,3876	0,6997
$\Delta(\log(\text{FN}))$	0,0016	0,0049	0,0084	0,3302	0,7424
$\Delta(\log(\text{LF}))$	0,0413	0,0397	0,0226	10,417	0,3016
DummyCOVID19	-0,0022	0,0026	-0,0087	-0,8524	0,3973

F: 0.2018; Adjusted R2: -0.0644

According to the results of the Ridge regression model, the explanatory power of the independent variables on stock price changes was found to be very low, with an adjusted R^2 of -0.0644. The model was not statistically significant overall (F-statistic = 0.2018, $p > 0.05$), and none of the independent variables had statistically significant coefficients. The lowest p-value was observed for the $\Delta(\log(\text{LF}))$ variable ($p = 0.3016$), which remains above the 5% significance threshold and is therefore not considered statistically significant. Among the independent variables, the highest standardized beta coefficient belonged to $\Delta(\log(\text{LF}))$ (0.0226), while the effects of the other variables were considerably weaker. The DummyCOVID19 variable had a negative coefficient (-0.0022), but it was not statistically significant either ($p = 0.3973$). Although the Ridge regression method effectively reduced multicollinearity, it did not result in statistically significant effects of the independent variables on stock prices (Karagöz, 2016).

Table 5.20. ARDL Model Estimation Results for Turkish Airlines

Variable	Beta	Std. Error	t-value	p-value
Coefficient (Intercept)	1.02E-17	9.20E-18	1.105	0.273
$L(\Delta(\log(\text{SP})), p_best)$	1.000	7.28E-17	1.37E+16	<2e-16 ***
$L(\Delta(\log(\text{RPK})), q_best)$	6.90E-18	1.06E-16	0.065	0.948
$L(\Delta(\log(\text{PAX})), q_best)$	1.33E-16	3.17E-16	0.420	0.676
$L(\Delta(\log(\text{FN})), q_best)$	-1.37E-16	2.74E-16	-0.499	0.620
$L(\Delta(\log(\text{LF})), q_best)$	-1.13E-16	3.89E-16	-0.290	0.773
DummyCOVID19	-1.13E-17	1.81E-17	-0.626	0.534

RSS: 4.65e-18; F: 0,653; Adjusted R2: 1; F: 5.038e+33; $p < 2.2\text{e-}16$

According to the ARDL model estimation results, the lagged value of the dependent variable ($\Delta(\log(\text{SP}))$) was found to be statistically significant ($p < 2e-16$), with its coefficient estimated as 1. However, all other independent variables had p-values greater than 0.05 and were not statistically significant. The R^2 and adjusted R^2 values were both equal to 1, indicating that the model explains the entire variation in the dependent variable. Nonetheless, this may point to a potential overfitting issue. Although the F-statistic was extremely high ($1.37e+16$) and the model was found to be statistically significant overall ($p < 2.2e-16$), the lack of significance among the independent variables raises concerns regarding the model's reliability. Despite this, the model was accepted based on the lag structure selected according to the Akaike Information Criterion (AIC) (Contuk & Güngör, 2016).

Table 5.21. UECM Model Estimation Results for Turkish Airlines

Variable	Beta	Std. Error	t-value	p-value
Coefficient (Intercept)	3,39E-15	2,08E-31	1,63E+19	<2e-16 ***
$L(\Delta(\log(\text{SP})), p_best)$	1.000	1,98E-30	5,05E+35	<2e-16 ***
$L(\Delta(\log(\text{RPK})), q_best)$	3,68E-16	2,17E-30	1,70E+17	<2e-16 ***
$L(\Delta(\log(\text{PAX})), q_best)$	2,07E-15	2,59E-30	7,98E+17	<2e-16 ***
$L(\Delta(\log(\text{FN})), q_best)$	-1,37E-15	3,49E-30	-3,92E+17	<2e-16 ***
$L(\Delta(\log(\text{LF})), q_best)$	-2,67E-15	4,33E-30	-6,15E+17	<2e-16 ***
DummyCOVID19	-7,41E-16	5,37E-31	-1,38E+18	<2e-16 ***
Error Term (ECT)	1.000	4,15E-14	2,41E+19	<2e-16 ***

RSS: 2.224e-32; F: 0,653; Adjusted R^2 : 1; F: 2.46e+62; $p < 2.2e-16$

According to the UECM model estimation results, the lagged value of the dependent variable ($L(\Delta(\log(\text{SP})), p_best)$) and all lagged values of the independent variables ($L(\Delta(\log(\text{RPK})), q_best)$, $L(\Delta(\log(\text{PAX})), q_best)$, $L(\Delta(\log(\text{FN})), q_best)$, $L(\Delta(\log(\text{LF})), q_best)$) were found to be statistically significant ($p < 2e-16$). However, the magnitude of the coefficients and the scale of the residuals indicate that the model may be overfitted. The error correction term (ECT) was calculated as 1, which suggests an excessively rapid speed of adjustment toward equilibrium, raising concerns about

the reliability of the model in representing long-run relationships. The extreme significance of all coefficients, combined with very small residuals, points to a possible structural misspecification or overparameterization within the model.

Table 5.22. RECM Estimation Results for Turkish Airlines

Variable	Beta	Std. Error	t-value	p-value
Coefficient (Intercept)	2E+01	2E+01	2E+03	1E-01
$\Delta(\log(\text{RPK}))$	-2E+01	2E+02	-1E-01	9E-01
$\Delta(\log(\text{PAX}))$	-9E+02	5E+02	-2E+03	0,0914
$\Delta(\log(\text{FN}))$	9E+02	5E+02	2E+03	0,0519
$\Delta(\log(\text{LF}))$	2E+03	7E+02	2E+03	0,0172*
DummyCOVID19	-2E+01	3E+01	-7E-01	5E-01
Error Correction Term (ECT)	-3E+03	2E+17	0,000	1,000

Adjusted R²: 0.03837; F-statistics: 1.439; Model p-value: 0.215

According to the RECM model estimation results, the model demonstrated low explanatory power in capturing the short-term dynamics of stock prices (Adjusted R² = 0.04204). The F-statistic was calculated as 1.483, and the overall significance of the model was not statistically acceptable ($p = 0.1995$). An examination of the short-term coefficients revealed that the load factor ($\Delta(\log(\text{LF}))$) was statistically significant at the 5% level ($p = 0.0172$), indicating that the load factor positively influences stock prices. The number of flights ($\Delta(\log(\text{FN}))$) was found to be marginally significant at the 10% level ($p = 0.0519$), while the number of passengers ($\Delta(\log(\text{PAX}))$) was also considered borderline significant at the 10% level ($p = 0.0914$). The remaining variables were not statistically significant ($p > 0.05$). The error correction term (ECT) was estimated as -3.176; however, it was not statistically significant ($p = 1.000$). Overall, the model demonstrated weak fit, suggesting that the short-term variables do not have a clearly defined impact on stock price movements (Tari, 2015).

Table 5.23. Results of Hypothesis Tests

No	Hypothesis	Accept/Reject
H _{A.1}	ASKs of airline companies significantly impact their stock prices.	Reject
H _{A.2}	RPK of airline companies significantly influences their stock prices.	Reject
H _{A.3}	PAX carried by airline companies has a significant effect on their stock prices.	Reject
H _{A.4}	FN operations by airline companies significantly affect their stock prices.	Reject
H _{A.5}	The LF of airline companies has a significant effect on their stock prices.	Accept
H _{A.6}	The variable reflecting the impact of the COVID-19 pandemic significantly affects airline companies' stock prices.	Reject
H _{A.7}	Airline companies' stock prices are significantly influenced by their historical stock prices.	Accept

5.11. Discussion

The findings obtained in this study suggest that the impact of operational performance indicators on airline stock prices may be limited. Among these indicators, the load factor (LF) appears to be the most obvious variable, as it reflects the revenue efficiency of the airlines and is the most visibly transferred to stock prices. A study conducted on five Indian civil aviation companies indicated that the main value determinants of firms did not show sudden or large fluctuations; however, the sensitivity of corporate cash flows to lockdown restrictions during the pandemic varied depending on the firms' cost structures (Mohanty & Mishra, 2023). This emphasizes the critical importance of managing capacity utilization in the high fixed-cost characteristic of airline businesses. Another study, which evaluated annual data from 134 airline companies between 2007 and 2019, suggested that aircraft leasing is a strategic tool for improving operational efficiency. The study showed that leasing arrangements can offer a significant advantage by enabling airlines to respond more flexibly to crisis situations such as the COVID-19 pandemic (Bourjade & Muller-Vibes, 2023).

The lack of a statistically significant relationship between other operational performance indicators, such as ASK, RPK, PAX, and FN, and stock prices suggests that operational scale alone may not be a sufficient indicator for investors in times of

crisis, such as COVID-19. The dynamic panel and time-series models used in this study revealed that stock prices are largely influenced by their own past values. This finding indicates that behavioral factors in the market (e.g., trend-following) and macroeconomic risks play a guiding role in investment decisions.

The finding that the sudden shock caused by the COVID-19 pandemic did not cause a long-term lasting effect suggests that the airline industry has a strong potential for recovery following crises. On the other hand, another study reported that airline companies experienced difficulties in recovering after the pandemic (Cavallaro & Nocera, 2024). Nevertheless, enhancing operational flexibility and financial risk management practices seems to be essential for achieving sustainable performance in crisis scenarios. In a study examining the financial outcomes of airlines during the COVID-19 pandemic, the role of speculation, government bailout packages, and expansionary monetary policies was examined. While increases in credit risk premiums and borrowing costs were observed, government support packages were found to be critical in stabilizing the sector, with a return to pre-pandemic load factors reported as of March 2021 (Costa et al., 2024). This finding is consistent with the results of this study.

Another study that used machine learning methods, such as Random Forest and Stochastic Gradient Boosting, to analyze the pandemic's impact on airlines indicated that the aviation sector is highly vulnerable to external shocks (e.g., pandemics), with increased financial trouble risks. Debt-to-equity ratio, return on investment, and leverage ratio were identified as the most critical indicators in such environments (Halteh et al., 2024). Similarly, a comparative study on Chinese and U.S. airlines separated the pandemic timeline into stages—outbreak, disruption, adaptation, and restructuring—and suggested that temporary policies such as reducing flight frequency could support faster recovery of air transportation (Li et al., 2023). The study also found that increasing load factors by reducing flight frequency could contribute to cost efficiency and provide a competitive advantage in stock price performance.

In a separate study that employed LASSO regression and other machine learning techniques to predict airline stock closing prices, past closing prices were found to have a significant impact on current prices. It was also highlighted that airline stock

prices are influenced not only by internal dynamics but also by macroeconomic and financial factors (Xu et al., 2023). These findings align with this study's dynamic panel model results, which also revealed strong effects of lagged values. Moreover, to address multicollinearity, Ridge regression—similar in nature to LASSO—was applied.

In another study analyzing the macroeconomic factors affecting airline stock prices, the Toda-Yamamoto and Hatemi-J asymmetric causality tests were utilized. The results revealed significant causal relationships between airline stock prices and both the exchange rate and oil prices (Alici, 2024). The study also emphasized that investment in alternative fuel technologies by the airline industry could serve as a hedge against oil price risks, while emphasizing the importance of continued government support.

Riley et al. (2003) examined how non-financial performance metrics impact stock prices in the airline industry. The findings showed that non-financial factors, like higher load factors (LF) and increased capacity, are positively linked to stock performance. Turturea & Turcu (2015) examined how non-financial indicators can improve performance measurement in the airline industry. By analyzing data from 32 international airlines (2006–2013), they found that indicators like load factor and available seat kilometers significantly affect stock prices. In his early research, Alici (2020) investigated the factors influencing stock prices in the airline industry by examining operational, financial, and macroeconomic variables. The findings revealed that operational indicators like load factors (LF), revenue passenger kilometers (RPK), and cost per available seat kilometer (CASK) significantly affect stock prices. In this study, it is also found that load factor (FK), one of the operational performance indicators, had a positive and statistically significant effect on all examined airlines' stock prices during the COVID-19 period. Hence, the findings of previous research partially support the results of this study.

Considering together, these findings suggest that the valuation of airline companies in the eyes of investors does not solely depend on operational performance, but also on the broader macroeconomic environment, corporate strategy, and financial management policies.

CHAPTER VI

CONCLUSION AND SUGGESTIONS

This study was conducted to examine the impact of airline companies' operational performance indicators on stock prices and was analyzed using various econometric methods. The main findings suggest that operational variables have a limited ability to explain stock price movements. This indicates that the operational success of airline companies does not directly convert to stock market performance, and macroeconomic and financial factors play a significant role in investor decisions.

An examination of trends in indicators such as ASK, RPK, PAX, FN, and LF reveals that the COVID-19 pandemic had a dramatic impact on operational performance starting in March 2020. All airline companies experienced a sharp decline, although the pace and magnitude of recovery varied. Turkish Airlines indicated a faster post-pandemic recovery compared to its peers, while American Airlines and Lufthansa experienced a more volatile recovery period. In terms of stock price performance in U.S. dollars, it is observed that, as of 2024, Turkish Airlines has surpassed its pre-pandemic valuation by a noticeable margin, whereas other airlines still appear to struggle to recover their pre-COVID levels.

Based on the analysis of the relationship between operational performance indicators and stock prices of airline companies under the effect of COVID-19, the following key findings were obtained:

- The load factor (LF) is the most influential operational performance indicator affecting stock prices.
- Airline stock prices are largely influenced by their own past values.
- ASK, RPK, PAX, and FN were not found to have a statistically significant impact on stock prices.
- The impact of the COVID-19 pandemic on stock prices was examined across multiple models, and in general, although there are short-term effects, the

pandemic did not have a statistically significant or persistent effect in the long term.

Overall, the study demonstrates that the influence of operational performance indicators on stock prices is limited, and that other financial and macroeconomic factors play a critical role in determining stock valuations. Future research is suggested to explore the longer-term effects of operational indicators and to further investigate the relationship between stock prices and economic variables.

According to the results of the analysis, the load factor stands out as the most influential operational variable affecting stock prices. The primary reason for this is that load factor directly reflects revenue efficiency. Considering the capital-intensive nature of airline operations with high fixed costs, profitability increases as capacity utilization increases. Investors closely monitor how efficiently airlines utilize their passenger-carrying capacity, which makes load factor a critical determinant in market valuation.

Airlines should prioritize load factor efficiency to better associate with investor expectations and maintain stability in stock prices. Methods such as dynamic pricing strategies, seat capacity optimization, and loyalty programs can improve load factors and strengthen the financial value of the company.

The study findings also indicate that airline stock prices are greatly influenced by their own past values. This suggests that market participants build their investment decisions on historical data and current trends. Uncertainties in the airline industry—such as fuel price volatility, regulatory changes, or economic downturns—may encourage investors to implement a more careful pricing strategy.

To build investor confidence, airlines should make transparent financial reporting, conduct regular investor briefings, and provide clear market guidance. Furthermore, investor relations departments should act proactively to communicate with investors to help mitigate the impact of market fluctuations and contribute to the stability of stock prices.

The analysis also shows that variables such as flight capacity, revenue passenger kilometers, number of passengers, and number of flights do not significantly affect stock prices (Apaydın & Aksoy, 2025). This is likely because these indicators have only an indirect impact on stock performance and are insufficient to drive investor decisions. For instance, an airline may carry a high number of passengers but may still show weak financial performance.

To attract investor interest and enhance the impact of operational performance on stock prices, airline companies should focus more on revenue-based metrics, such as unit revenues, profitability margins, and cost per passenger. They should emphasize not only operational scale but also operational efficiency and financial productivity in annual reports and investor presentations to help improve investor perception.

The COVID-19 pandemic represented an extreme shock to the airline industry. Beginning in March 2020, airline companies experienced sharp declines in both operational indicators and stock prices. However, the analysis indicates that the effects of the pandemic were not statistically persistent in the long term. This can be primarily credited to post-pandemic government aid measures and economic recovery efforts, which provided financial support to airlines; the gradual reduction of international travel restrictions through vaccination; the revival in demand; and airlines' ability to re-optimize costs and provide operational sustainability.

To develop a more resilient business model for future global crises, airline companies should strengthen their crisis management strategies. The following recommendations are proposed:

- Enhance flexible capacity management and route optimization practices.
- Use hedging instruments to protect against fuel price volatility.
- Increase investments in digital transformation and automation to improve operational efficiency.

While this study focuses on the effects of operational indicators on stock prices, other macroeconomic and financial variables influencing airline stock performance were not addressed. Future research could explore the following areas:

- Analyzing the impact of fuel prices, exchange rates, and interest rates on airline performance.
- Investigating the influence of government aids, regulatory changes, and sustainability investments on investor perception.
- Applying next-generation forecasting models, such as machine learning and deep learning, to predict stock prices using both operational indicators and economic variables.

This study provided a detailed analysis of how operational performance indicators affect airline stock prices, highlighting load factor as the most critical variable in terms of financial performance (Apaydın & Aksoy, 2025). However, it is essential to acknowledge that investor decisions are shaped not only by operational metrics but also by macroeconomic developments and financial risks. For airline companies to build a more robust financial structure in the future, they should prioritize operational efficiency, financial risk management, and strategic resilience in times of crisis.

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