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Impact of Covid-19 Pandemic on the U.S. Aviation Market

Bachelor's thesis

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Declaration of Authorship

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Prague, May 3, 2023 Lilit Mehrabyan

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Abstract

In 2020, COVID -19 spread through the whole world causing social and economic disruption. Industries reliant on human interaction such as hospitality, healthcare, tourism and especially the aviation industry were severely affected. The following thesis aims to examine the impact of the virus on the U.S. aviation market. To estimate the causal effect of the pandemic on the performance of low-cost and full-service U.S. carriers, a set of OLS regression models were developed using relevant macroeconomic and additional binary control variables. In each of the regression model the explanatory variable COVID-19 was estimated uniquely, enhancing the accuracy of the model. The results imply that the negative effect of COVID-19 variable on revenue passenger mile (RPM) of full-service carriers was higher than for low-cost airlines.

Keywords	COVID-19, airline market, OLS regression, low-cost carriers, full-service airlines
Title	Impact of Covid-19 Pandemic on the U.S. Aviation Market

Abstrakt

V roce 2020 se COVID-19 rozšířil do celého světa a způsobil sociální a ekonomický rozvrat. Těžce postižena byla odvětví závislá na lidské interakci, jako je pohostinství, zdravotnictví, cestovní ruch a zejména letecký průmysl. Následující práce si klade za cíl prozkoumat dopad viru na americký letecký trh. Pro odhad kauzálního účinku pandemie na výkon nízkonákladových a kompletní servis amerických dopravců byla vyvinuta sada regresních modelů OLS s použitím relevantních makroekonomických a dalších binárních kontrolních proměnných. V každém z regresních modelů byla vysvětlující proměnná COVID-19 odhadnuta jednoznačně, čímž se zvýšila přesnost modelu. Výsledky naznačují, že negativní vliv proměnné COVID-19 na příjmové míle (RPM) dopravců s kompletními službami byl vyšší než u nízkonákladových leteckých společností.

Klíčová slova COVID-19, letecký trh, OLS regrese, nízkonákladoví dopravci, Kompletní servis letecké společnosti

Název práce Dopad pandemie Covid-19 na americký letecký trh

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Acronyms

LCC Low-cost carrier
FSC Full-service carrier
BTS Bureau of Transportation Statistics
ICAO International Air Transport Association
IATA International Air Transport Association

1. Introduction

Airline industry has played a crucial role in the development of the global economy. Not only by providing an efficient and accessible transportation network, which promotes tourism and international trade, but also employing 11.3 million people directly, and 87.7 million people indirectly as of pre Covid-19 pandemic figures (Air Transport Action Group, 2021). Since 1950s there has been a significant increase in the number of passengers carried per year, growing from less than 50 million in 1950 to 4,5 billion passengers in 2019 (ICAO, 2021). As a result, the global market size of the aviation industry reached almost $820 Billion in 2019 (Statista, 2021).

The growth of the aviation industry however has not been steady. Several global events directly or indirectly have impacted the industry, causing discrepancies in the development. Oil crisis in 1973, Iran-Iraq war in 1980, Gulf crisis in 1990-1991, Asian crisis in 1998, the 9/11 terrorist attack in 2001, SARS outbreak in 2003, financial crisis in 2008 are the largest events that have negatively impacted the demand, thus decreasing the key figures of aviation (ICAO, 2019). The latest crisis which led to massive loses in the whole industry is the Covid-19 pandemic. Covid-19 pandemic has had a crucial effect on the whole world becoming detrimental to many sectors ranging from Leisure and Hospitality to Manufacturing, Construction and Health Care (McKinsey & Company, 2020). However, it is evident that as soon as the virus started spreading through the world the first reaction of most of the countries was to put entry restrictions and close down the borders to curb the virus. This led to The Global Aviation Sector to suffer $32 Billion Economic Loss in 2020 (ICAO, 2021).

Multiple researchers have studied the impact of Covid-19 on the Aviation Industry, by tracking the traffic modules (Dube et al., 2021), flight frequencies (Liu et al., 2021), or by estimating the potential loss of the world GDP caused by the reduction in the aviation activity (Iacus et al., 2020). A few studies were conducted to analyze the US aviation market, examining the financial losses of the 10 largest companies based on their operational strategies (Fontanet-Pérez et al., 2022). The key conclusion drawn from all of the research is that the severe circumstances following the spread of the virus caused global aviation market to face great financial challenges by losing significant revenues in 2020.

The impact of COVID-19 on the airline companies was not uniform. There is a key operational difference, which divides the airline companies into 2 main categories: full-service and low-cost. Thus, the main objective of the following thesis is to thoroughly analyze the performance of the US aviation market during the Coronavirus disease by separately investigating and comparing the impact of the pandemic on both low-cost and full-service airline companies. Several reports indicate that low-cost airlines have experienced lower financial losses as a result of the virus than full-service airlines (Stanojevic et al., 2021; Jimenez et al., 2020), although to our knowledge, no regression study has been carried out. Therefore, in the following thesis we took a 10-year timeline and employed an Ordinary Least Squares regression method to assess the impact of COVID-19 pandemic on the performance of low-cost and full-service airlines in the US market.

This thesis is organised as follows. The Chapter 2 provides information on two main types of airline companies, discussing the general strategic approach and revenue source. Additionally, the Covid-19 impact on the U.S. airline industry is highlighted. Chapter 3 presents the literature review on general impact of the virus on the airline industry and more specific studies which put difference between low-cost and full-service airlines. Chapter 4 summarizes the data used in the analytical part of the thesis and in Chapter 5 we provide the descriptive statistics of the outcome variables. Chapter 6 is dedicated for the methodology and respectively Chapter 7 is based on the results and interpretation. Chapter 8 concludes the following research.

2. Commercial Aviation and U.S. Airline Market During COVID-19

2.1 Types of Airline Companies

Commercial airline companies divide into 2 main categories. There are full-service airlines and low-cost airlines. There are more underlying disparities from an operational standpoint in addition to the obvious discrepancies in the supplied fares, which is one providing more affordable service than the other.

There is a difference in the strategic approach of the airlines. Firstly, the low-cost airlines tend to focus on shorter and more demanded roots, while full-service airlines put the priority on the network connections. The shorter flights allow LCC's such as Ryanair, EasyJet or JetBlue to perform frequent direct flights and optimize the time that the airplane stays on the ground. Meanwhile, FSC s often perform flights corresponding to the hub and spoke model, requiring layovers until the final destination is reached (Almeida et al., 2023).

Minimizing any costs required to perform a flight is the primary goal of the low-cost carriers. As a result, utilizing a secondary airport which is located further from the city center is more affordable for the airline company but is still attractive to the customer. In contrary, FSCs lend in the larger airports, equipped with better facilities and with higher ground fees. For instance, a well-known full-service airline Air France lands at the Charles de Gaulle Airport in Paris, meanwhile Ryanair uses the Beauvais Airport which is located 80km away from Paris (Curran, 2022).

While charging low fares, low-cost airlines maximize the capacity of the aircraft, leaving little leg room for the passengers. Any additional services, such as checked baggage, food, or seat selection prior to boarding, are charged extra, resulting in the larger portion of the profit of the airline companies. A profit which is earned in addition to the sold ticket is called ancillary revenue, and as of 2021 low-cost airlines Wizz Air, Frontier, Spirit and Allegiant generated more than 50% profit from ancillary revenue (CarTrawler, 2022).

2.2 U.S. Airline Market and Covid-19

From 4.5 billion of overall number of scheduled passengers in 2019, 925.5 million passengers were carried by U.S. airlines (ICAO, 2020; BTS, 2020). For comparison the largest U.S. low-cost airline, Southwest, carried 134.1 million passengers in 2019, accounting for 16,9% of the U.S. market share, while American Airlines, which is a full-service carrier, held the most market share with 17.6% (Southwest, 2020; BTS, 2023). The following numbers changed drastically in 2020.

The first Covid-19 case in U.S was recorded on January 30, 2020, already by the end of August there were more than 5 million recorded cases, and the virus became the third most common cause of death in the states. Starting from March 15, the U.S. government started implementing lockdowns for the purpose of prevention of the virus (CDC, 2022). As a result, in 2020 the U.S. market faced the highest record of cancelled flights recorded in the last 20 years, with around 280 thousand cancelled flights (Statista, 2022). Overall, the number of passengers carried by the U.S. airlines in 2020 dropped by 60% in comparison with 2019 by carrying only 369 million passengers (BTS, 2021). The U.S airlines lost $35 billion after-tax net-income, in comparison with $14.7 profit in 2019 (BTS, 2021).

Specifically, the largest U.S. low-cost airline in 2020 experienced annual net loss of $3.5 billion, excluding net special items, while the largest full-service airline American Airlines faced $9.5 billion net loss, excluding net special items (Southwest, 2021; American Airlines, 2021). Jimenez and Sau-Sanchez (2020) found that generally LCCs were faced by less financial losses caused by the pandemic, because of the small number of long-distance flights.

3. Literature review

3.1 General Research of Aviation market during Covid-19

The key finding, according to Sun, Wandelt, Zheng, Zhang (2021), is that while the airline industry was one of the sectors that were most severely affected by the Covid-19 outbreak, it was also responsible for the virus's spread. The transportation sector functions as a vast network due to technological advancements, increased globalization, and the high volume of everyday travelers. The average travel time is far less than the duration of the incubation period of the infectious diseases (Budd et al., 2009). As previously observed with Ebola, SARS/MERS, seasonal influenza and Malaria/Dengue fever air travel plays one of the crucial roles in the spread of the diseases. The Global epidemic and mobility computational model, the vector-borne disease airline importation risk model, and other Susceptible-Exposed-Infectious-Recovered based models using airline data have all been developed with the aim of trying to identify the roles of airports and air travel in the spread of common infectious diseases.

Variables such as Airline Traffic, Passenger Traffic, and Freight Traffic are often used by experts to measure the possible impact of significant events on the aviation industry. Maroof, Naz and Jaward (2021) in their journal applied two models separately, setting the independent variable Covid cases in one, and Covid deaths in the other, to test the possible economic impact of the Covid-19 on airline companies. The results of Multiple Panel data analysis using data from 10 Eurasian countries, revealed the positive influence of Covid cases on Freight Traffic, meanwhile the Passenger traffic experienced much larger decline.

Sandro Nižetić (2020) based his study of the impact of Covid-19 on two Croatian airports. The chosen airports differed in their operational nature. With over 3.4 million passangears annually, the first airport, Zagreb, is the busiest in Croatia and is similar to a standard airport in the EU (Zagreb Airport, 2021). While the second airport, the Split airport, is considered as a seasonal airport and is located on coast of Adriatic Sea, with overall 3.3 million passages per year (Split Airport, 2020). While airline activity at Split Airport increases during the summer, it is more evenly distributed at Zagreb Airport throughout the year. By the conducted comparison of air traffic, it was evident that the number of flights started declining since January 2020, which corresponds to the time when the virus began spreading through the EU. The largest decline in flight traffic in Zagreb was observed in April 2020, with a loss of 96.9%. Split Airport, on the other hand, had a 100% decline in flight traffic, leaving the airport completely empty. That can be accounted for by the fact that the Split airport is mainly used by tourist with the purpose of traveling.

The model Multicriteria Data Envelopment Analysis (MCDEA) was used by Carlos and Soares (2021) to evaluate the effectiveness of airline companies in the Brazilian domestic air transport industry during the Covid-19 outbreak. The MCDEA model is an improved version of the traditional Data Development Analysis (DEA) model established by Li and Reeves (1999). Three major Brazilian airlines were chosen to perform the analysis. The number of aircraft takeoffs, fuel consumption, and the available ton kilometers were chosen as the input factors, and the revenue ton kilometers was the output variable. Each airline operates a different kind of aircraft, thus the diversity in operation and fuel consumption was also taken into account. The three companies' efficiency values were at their lowest in March 2020, when the WHO proclaimed the Covid-19 outbreak a global pandemic. Even with an average drop in takeoffs and RTK (revenue ton kilometer) between February and March of 2020 of 25% and 32%, respectively, the firms were unable to effectively address the Covid-19 outbreak restrictions.

According to Coelho et al. (2020), the virus was far more likely to spread swiftly in larger urban areas with a higher population and more linkages to the outside world. A standard multiple regression model was used for the investigation, and it was employed to determine the effective distance between Brazilian microregions and the likelihood of an epidemic occurring there.

3.2 Economic based literature

Fontanet-Pérez, Vázquez and Carou (2022) using data from Bureau of Transportation Statistics and 10-K/A reports examined 10 US airline companies to analyze the financial losses that the companies suffered as a result of Covid-19 virus. The subjects of the research were 4 full-service, 3 low-cost and 3 ultra-low-cost airline companies. The results indicated that full-service airlines faced higher losses in comparison with low-cost and ultra-low-cost airlines. The Net Income Variation value of full-cost airlines have dropped by higher values such as by 300% - 500% while for low cost the drop was estimated around 150% - 300%. The reason is suggested to be the fact that the full-service airlines found to be less adaptive to drastic changes in the market. Suau-Sanchez, Voltes-Dorta, Cugueró-Escofet (2020) who based their research on both international and domestic market of airlines from across the world also found that low-cost carriers suffered less losses in comparison with full-cost airlines. Based on the Available Seat Kilometer Index's year-over-year change, LLC had a decline in March of around 50.6%, whilst FSNC experienced a loss of about 70%. In the following thesis, the aim is to investigate how the Covid-19 affected both full cost and low-cost airline companies based in United States. Consequently, we will determine whether low-cost airlines will suffer less than full-cost airlines as seen in the event of financial losses.

Similar results were found by Stanojevic, Mitic, Radiovojevic (2021) who aimed to assess the economic and financial impact of Covid-19 on airline industry, by analyzing 5 largest

European airline companies, covering 5 years prior to the pandemic as well. Using the data from balance sheets and income statements provided by each individual airline company they estimated that the financial losses faced by full cost airlines (Lufthansa, AirFrance) is higher in comparison to low-costers (easyJet, Ryanair). The values of the Return on Equity were the primary indicators of the low profitability in the subsequent study. In 2020, Lufthansa's ROE dropped to a negative value of 484.86, whilst Ryanair's ROE positively stood at 13.20. Whether the Covid-19 effect on the European aviation market is similar to the impact on US airlines, we will be able to determine in the following paper.

The significance of COVID-19 and other time-varying and invariant variables in explaining changes in intercity travel in China was examined by Li, Wang, Huang, Yang, and Chen (2021). Time-varying factors included determinants such as flight frequency, total confirmed cases, total recovered cases, while time-invariant factors included spatial distance, population, GDP etc. For the investigation, a gradient boosting decision tree model was utilized, which varies from typical statistical regression frameworks by not having predetermined linear assumptions. Three phases were observed: normal period, rapid decline period, and recovery period. First, the most significant independent variable determining intercity traveling was shown to be the total number of confirmed cases. The COVID-19 has influenced business growth and transportation connection, which both directly and indirectly decreases intercity travel. By incorporating factors like the intercity mobility index and monthly passenger volume into the analysis, Li, Cui, and Wang (2022) reviewed the findings of the aforementioned study and reached the identical results.

Zhang, Zhu and Hao (2022) studied the financial impact of Covid-19 on Airline industry of the Chinese market. For the analysis six sample airline companies were chosen, including both low-cost and full-service airlines. For the selected sample period starting from 1st of August 2019 to 15th of September 2021, the authors used multivariate regression model to measure the economic impact of Covid-19 on the stock prices of the chosen airline companies. They found that the impact of Covid-19 pandemic on stock prices of full-cost airlines was analogous, while for low-cost companies the effect was largely heterogenous. The following findings correspond to the observation of Maneenop and Kotcharin (2020). The value difference between the market value and the fair value of low-cost Chinese airlines ranged from 4% to 60%, while for full cost airlines the difference was a loss of around 55%. If the emphasis of our research is the revenue passanger mile, we will be able to examine if there will be any homogeneous or heterogeneous impacts on airline companies based on their operational strategy as shown in the case of stock prices.

Jimenez and Sau-Sanchez (2020) established the distinct difference of the Covid's effect on LCCs and FSNCs by a straightforward examination of data on supplied number of seats per month, of airlines from throughout Europe. In comparison to full service carriers, low-cost carriers had greater flexibility. The results demonstrated a more pronounced decline in the number of seats offered by FSNCs. As stated, due to the fact that low-cost businesses run on a greater number of roots, and since the virus propagated unevenly, their more diversified root systems benefited them.

Based on the literature review, the studies conducted on European, American and Chinese airlines, revealed that low-cost carries seemingly have suffered less losses from the Covid-19 pandemic then the full-cost airlines. The research were based on analyzing financial indicators, number of available seats, stock prices based on a shorter timeframe, and results up to 2021.

4. Data

In this thesis we used three different groups of data: civil aviation data, macroeconomic data and COVID-19 data. In this section describe the sources of each group and provide an overview of the variables collected.

4.1 Civil aviation variabes

The main source of the data for the US Airline companies is the Bureau of Transportation Statistics (BTS) database. BTS is a federal statistics agency that collects data from transportation industry, freight and commercial aviation. The main objective of BTS is to provide a reliable information on the various transportation segments in the US.

In this thesis I concentrate specifically on the U.S. carriers only. The data is published in Air Carrier Statistics (Form 41 Traffic)[1]. The data then is available in six databases:

1) T-100 Domestic Market
2) T-100 Domestic Segment
3) T-100 International Market
4) T-100 International Segment
5) T-100 Market (domestic and international T-100 market data)
6) T-100 Segment (domestic and international T-100 segment data)

One of the main distinctions between segment and market data is the scope of variables included under each representation. For instance, market data do not include flight capacity

[1] https://www.transtats.bts.gov/Tables.asp?QO_VQ=EED&QO_anzr=Nv4%FDPn44vr4%FDf6n6v56vp5%FD%FLS14z%FDHE%FDg4nssvp%FM-%FD%FDh.f.%FDPn44vr45&QO_fu146_anzr=Nv4%FDPn44vr45

or number of departures. The domestic and international segment databases contain more specific data, including number of scheduled and performed departures, cargo details, distance, airborne time, ramp to ramp time, type of aircraft, number of available seats, and number of passengers.

The two main sources of civil aviation data used are: T-100 Domestic Segment and T-100 International Segment. I collect the data for each flight performed by the US carriers in domestic and international segment over the period 2002-10-01 to 2022-09-01 for the variables:

1) SEATS – a number of installed seats in an aircraft exclusive of any seats not offered for sale to the public by the carrier
2) PASSENGERS – a number of non-stop segment passengers transported. This variable does not include members of the flight or cabin crew
3) DISTANCE – a distance between airports in miles
4) RPM – revenue passenger mile. This is a product of PASSENGERS and DISTANCE
5) ASM – available seat mile. This is a product of SEATS and DISTANCE. With this variable it is possible to identify the capacity of the routes of markets and measure the attractiveness of a given destination.

In the thesis we aim to compare low-cost and full-cost carriers and the effect of COVID-19 on their performance. Therefore, another piece of data which is the information on carriers that are included in the low-cost group is necessary.

For the list of low-cost carriers we used the ICAO data from the official web-site[2]. Whether a carrier is low-cost or full cost is indicated with the binary variable LOWCOST, which equals 1 for the low-cost carriers and 0 for the full-cost carriers.

4.2 Macroeconomic variables

In order to estimate the causal effect of COVID-19 pandemic on the performance of low-cost and full-cost US carriers it is necessary to control for the other variables that influence the industry and overall economy. For this reason, we used three control macroeconomic variables collected from the Federal Reserve Economic Data database[3]:

1) LABOR – Civilian labor force level measured as the number of people 16 years of age and older
2) UNRATE – Unemployment rate measured as the number of unemployed people divided by the labor force
3) FUEL – Producer Price Index for the Jet Fuel

4.3 Other variables

In addition to the macroeconomic variables listed above we use several binary variables that control for the seasonal or structural components in the series of civil aviation data and help to ensure additionally the correct causal effect estimation of COVID-19 pandemics.

Ito & Lee (2005b) suggested several binary control variables that can influence RPM as an outcome variable: war in Iraq and SARS pandemic.

[2] https://www.icao.int/sustainability/pages/low-cost-carriers.aspx
[3] https://fred.stlouisfed.org/

Other extraordinary events that affected the US Civil aviation industry are H1N1 (Swine flu) pandemics that lasted from April 2009 to August 2010. During that period US civil aviation faced a structural shift in the time series of RPM and ASM.

Two other important events affected US civil aviation market are merger of Continental Airlines to United Airlines in March 2012, and merger of U.S. Airways to American Airlines in October 2015.

The full list of the additional binary control variables includes:

1) LEAP – indicates leap years and equals 0.75 for February in leap year and -0.25 for non-leap February

2) SEAS – indicates high demand season and equals 1 for June, July, August (summer vacations) and December (Christmas holidays)

3) IRAQ – indicator for the period of Iraqi war, equals 1 for the period between 2003-02-01 and 2003-05-01, and equals 0 otherwise

4) SARS – indicator for the SARS outbreak, equals 1 for the period between 2003-03-01 and 2003-07-01, and equals 0 otherwise

5) SWINEFLU – indicator for the Swine Flu outbreak, equals 1 for the period between 2009-05-01 and 2010-01-01, and equals 0 otherwise

6) CONTI – indicator for the Continental merger, equals 1 for the period after 2012-03-01, and equals 0 otherwise

7) USAirw – indicator for the U.S. Airways merger, equals 1 for the period after 2015-10-01, and equals 0 otherwise

4.4 COVID-19 variables

This thesis studies the effect of COVID-19 on the U.S. civil aviation industry and, on the low-cost carriers in particular. Hence, the main independent variable of interest must represent the COVID-19 pandemic. Following Ito & Lee (2005a) I used three different versions of the variable of interest:

1) COVID19 – binary variable that equals 1 for the period after 2020-03-01, and equals 0 otherwise

2) COVID19m – a composite variable that includes both short and long-term effects of COVID-19 pandemics. This variable is constructed as:

$$\text{COVID19m} = \frac{1}{\text{Number of months since March 2020}}$$

For example, the variable COVID19m for April 2020 equals 1/2 and for June 2020 equals 1/4.

3) COVID19shock and COVID19post – binary variables representing separately the most severe period of COVID-19 pandemic (April and May 2020) and the post-shock period starting from June 2020 respectively. Therefore, COVID19shock equals 1 for only April and May 2020, while COVID19post equals 1 for the period from June 2020.

5. Descriptive statistics

In the previous section we described the main outcome variables used in the model: RPM and ASM together with the COVID-19 explanatory variables and the set of other control variables. In this section we concentrate on the descriptive statistics of the outcome variables: RPM and ASM for low-cost and full-cost U.S. Carriers.

We start the inspection of the variables with the overall dynamics of the series. Figure 5.1 clearly shows seasonality pattern and a slight upward trend over time. This fact must be accounted for when building regression models.

In March 2020 there is a sharp drop due to the COVID restrictions and the level of series still could not reach the pre-Covid values.

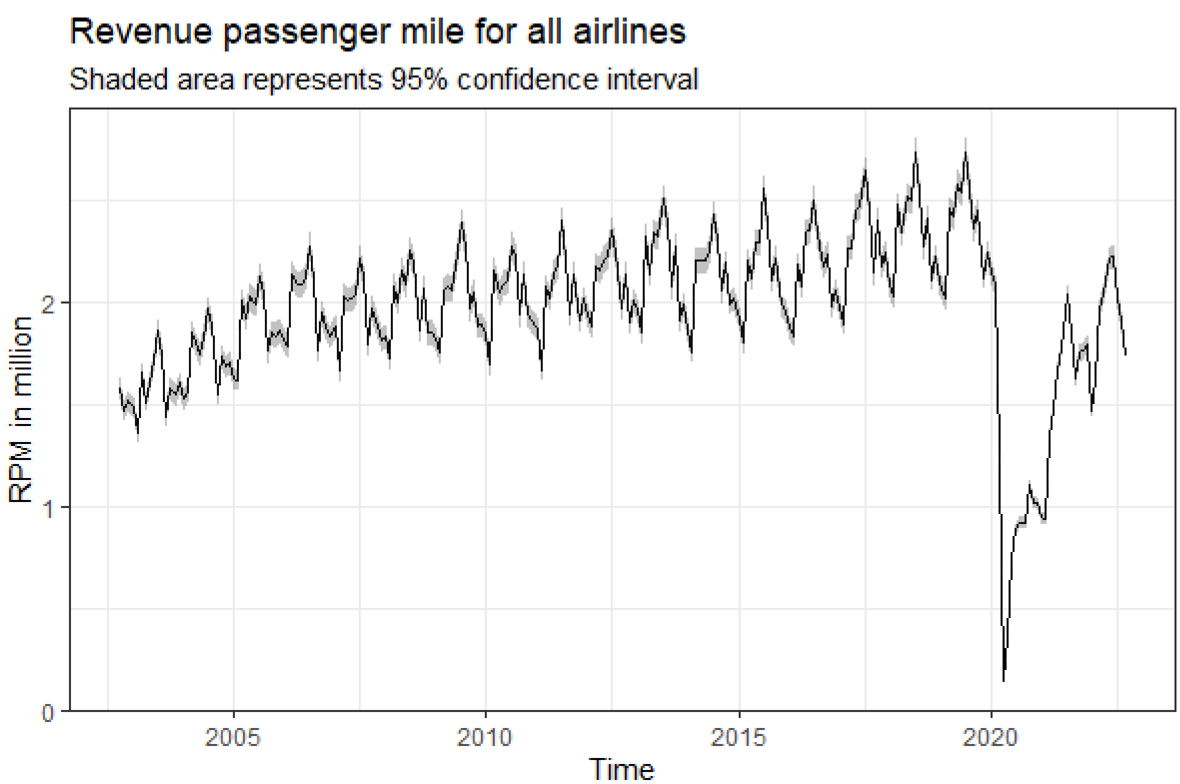

Figure 5.1. Revenue per mile dynamics for the U.S. Carriers

The figure 5.2 presents the separate RPM values for U.S low-cost and full-cost airlines.

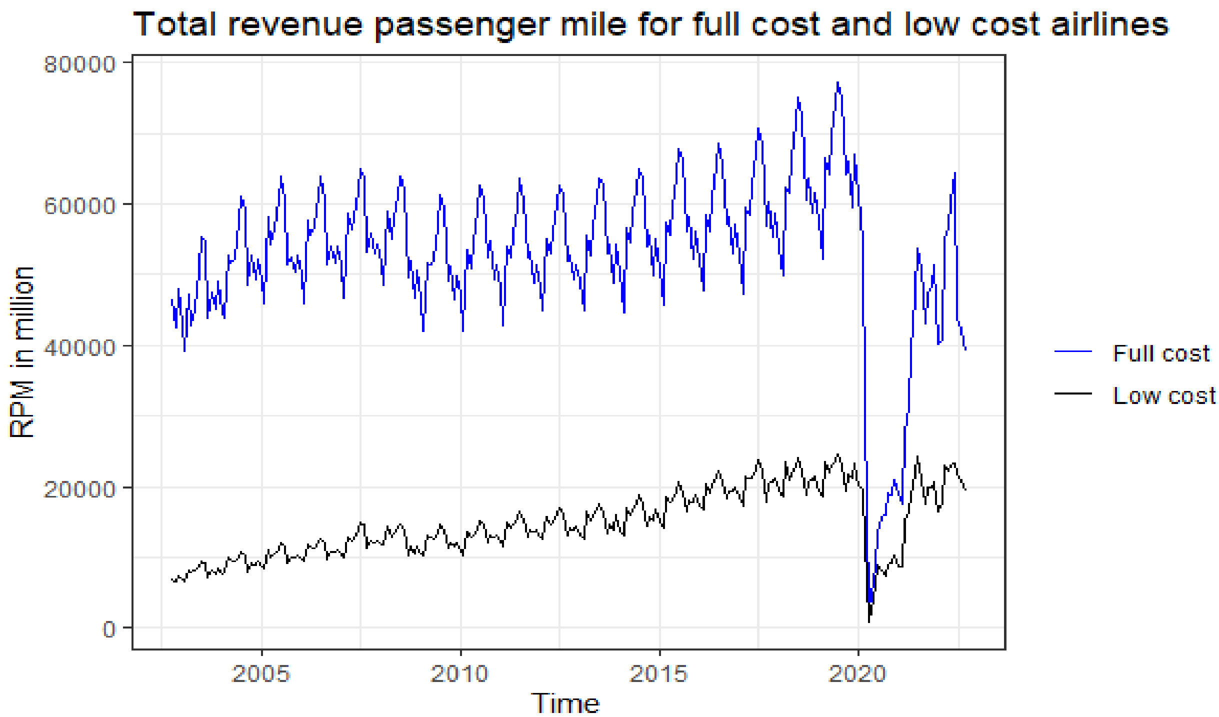

Figure 5.2. Revenue per mile dynamics for U.S. low-cost and full-service Carriers

The low-cost carriers generally exhibit lower RPM values, and seasonality swings are not as pronounced. Even though RPM value declined to nearly zero in both categories by 2020, the reduction was more drastic for full-service airlines.

For more detailed analysis we aggregated data over 5-year intervals that helps to better understand the dynamics and stationarity of the given series.

Each number in the table 5.1 represents statistics for airline-segment over one month. E.g. max RPM in 2002-2007 period is 156 885 358. This means that some airline in some segment transferred over one month in total 156 885 358 passengers x miles

PERIOD	Mean	SD	Min	10%	25%	50%	75%	90%	Max
2002/10-2007/12	1,698,061	5,658,280	0	0	0	37,278	810,568	3,915,886	156,885,358
2008/01-2012/12	1,900,273	6,083,478	0	0	124	69,641	926,786	4,296,770	172,828,758
2013/01-2017/12	1,991,316	6,259,650	0	0	140	86,362	1,020,924	4,652,478	193,903,740
2018/01-2022/09	1,811,402	5,635,919	0	0	0	69,580	1,012,176	4,365,348	157,671,500

Table 5.1. Summary statistics on Revenue per mile for low-cost U.S. Carriers

Table 5.1 displays the summary statistics on RPM for the low-cost U.S. Carriers. The average level of RPM gradually increases over the first 15 years and slightly drops in the last 5-year period. Almost quarter of the flights report zero RPM. There is also a strong left skewness of the data considering the large difference between medians (e.g. 37 278 in the first period) and means (e.g. 1 698 061 in the first period).

PERIOD	Mean	SD	Min	10%	25%	50%	75%	90%	Max
2002/10-2007/12	2,925,435	4,911,156	0	34,606	190,380	1,340,384	3,793,861	7,336,867	89,962,640
2008/01-2012/12	2,962,939	4,517,317	0	49,104	221,746	1,436,484	3,839,435	7,470,690	61,944,300
2013/01-2017/12	3,162,284	4,647,165	0	90,637	335,340	1,568,298	4,288,024	7,987,738	104,962,275
2018/01-2022/09	2,323,386	3,829,548	0	71,709	235,080	943,452	2,922,908	6,269,431	124,945,425

Table 5.2. Summary statistics on Revenue per mile for full-cost U.S. Carriers

Table 5.2 describes the same variable for the full-cost carriers. The dynamics of a mean suggests that the growth in RPM for the full-cost carriers was weaker than that of the low-cost carriers, while the decline in the last period is more pronounced.

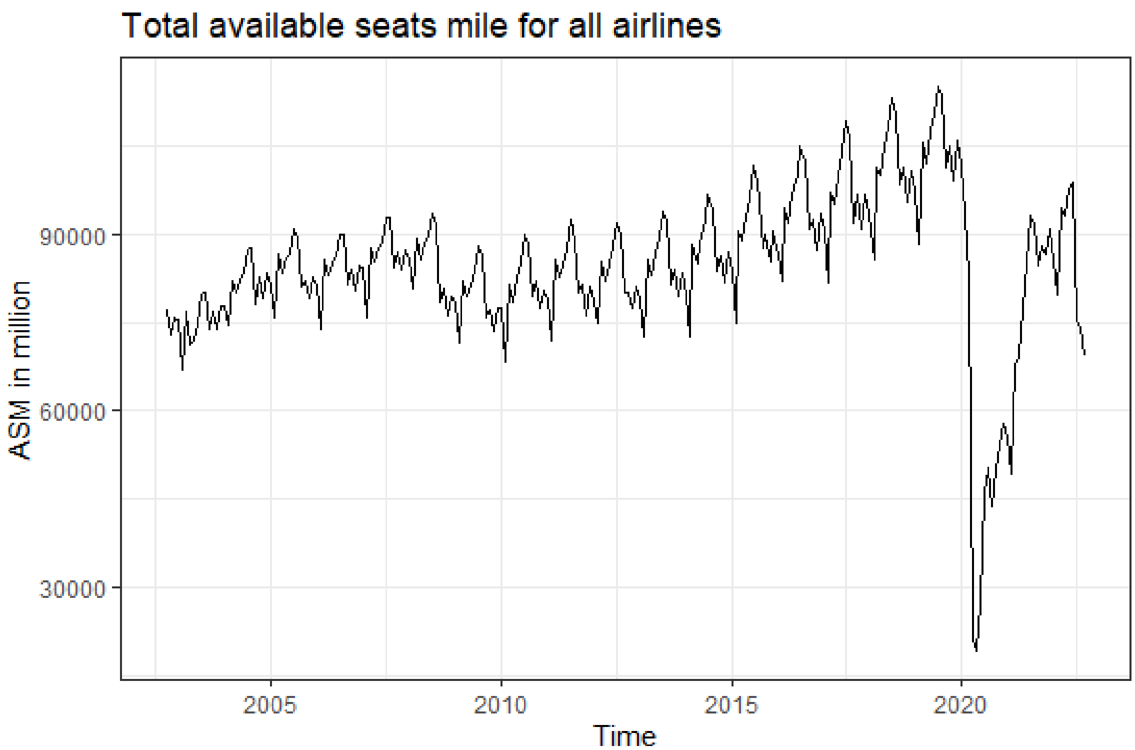

Figure 5.3. Available seats mile dynamics for the U.S. Carriers

The dynamics of ASM for all U.S. Carriers shows similar patterns as RPM series: seasonality, trend and sharp decline in March 2020. There is one distinction between ASM and RPM series: in the period between 2007 and 2012 ASM series have an U-shape, going down and then reversing back.

Figure 5.4 represents separately ASM of U.S. low-cost and full-cost carriers. As it was visible from the separate trendlines of RPM, low-cost airlines in average project lower values. Even though, ASM dropped almost to zero in 2020 for both cases, the drop of available seats of the full-cost airlines was from higher values then for low-cost carriers.

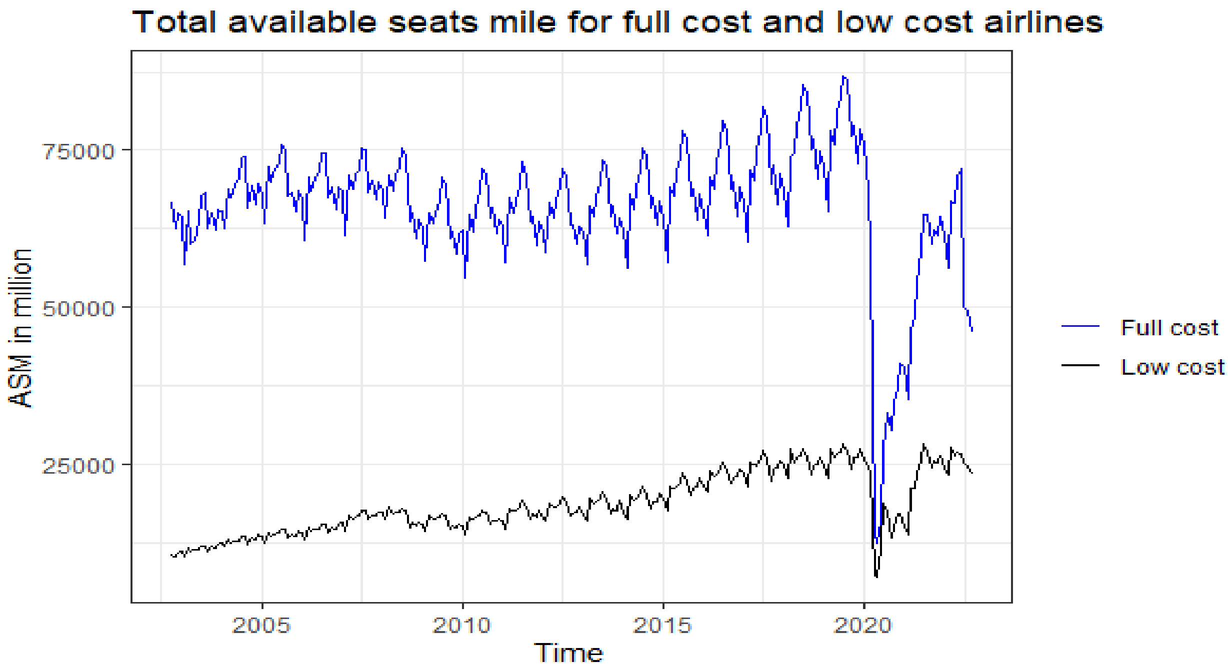

Figure 5.4. Available seats mile dynamics for the U.S. low-cost and full-cost carriers

Table 5.3 suggests almost stable mean number of available seats mile for the low-cost carriers with almost no decline in the last 5-year period and large difference between mean and median: an indicator of a high right-skewness of the distribution, that practically shows that the small number of airline segments possesses huge values of ASM.

PERIOD	*Mean*	*SD*	*Min*	*10%*	*25%*	*50%*	*75%*	*90%*	*Max*
2002/10-2007/12	2,190,019	6,897,781	0	0	346	73,800	1,178,200	5,269,316	162,438,822
2008/01-2012/12	2,327,082	7,202,271	0	0	1,062	114,750	1,242,000	5,372,136	215,391,816
2013/01-2017/12	2,394,940	7,378,198	0	0	1,428	133,200	1,286,208	5,610,405	209,855,475
2018/01-2022/09	2,313,089	6,875,094	0	0	1,035	127,800	1,379,040	5,698,560	176,168,000

Table 5.3. Summary statistics on Available seats mile for low-cost U.S. Carriers

PERIOD	Mean	SD	Min	10%	25%	50%	75%	90%	Max
2002/10-2007/12	3,985,590	6,073,341	0	78,638	279,851	2,054,178	5,423,282	9,839,232	95,365,920
2008/01-2012/12	3,722,307	5,374,369	0	83,590	302,760	1,912,800	4,979,128	9,354,012	75,432,474
2013/01-2017/12	3,781,554	5,345,628	0	1E+05	434,012	1,965,814	5,208,000	9,418,479	123,601,500
2018/01-2022/09	2,972,809	4,599,073	0	1E+05	353,850	1,310,400	3,852,744	7,857,144	152,460,000

Table 5.4. Summary statistics on Available seats mile for full-cost U.S. Carriers

Table 5.4 shows the gradual decline in mean ASM for the full-cost carriers. The decline accelerated in the last period which is more pronounced than that of low-cost carriers.

Considering tables 5.1 to 5.4 it is also possible to observe almost stable volatility of the series measured with the standard deviation. Given this, the seasonal (and other) factors do not impact the volatility of these indicators too much, and the industry displays the stable development over years.

6. Methodology and Main Time Series Models

The following chapter provides description of the models and the methodology used in the empirical part of the thesis.

We employed the Ordinary Least Squares (OLS) regression model, which is a commonly used method for times series regression analysis. We chose to use the OLS model because it is effective in assessing causality. The research conducted by Ito & Lee (2005a), Wooldridge (2013) and the thesis by Fedorik (2021) served as a base for forming our models.

Our models are based on the following static model which is for time-series data:

$$y_t = \beta_0 + \beta_1 z_t + \varepsilon_t, t = 1, 2, \dots, n$$

where:

y_t – Explained variable

z_t – Explanatory variable

ε_t – Random error term

To ensure that our regression model yields unbiased estimates with the smallest variance, it must satisfy the assumptions of Gauss-Markov. To make sure that our presumptions meet it would be beneficial to use one-month lag. Thus, we introduce the finite distributed lag model (FDL), which implies a linear relationship between several lags of an independent variable x and a dependent variable y.

$$y_t = \alpha + \beta_0 x_t + \beta_1 x_{t-1} + \varepsilon_t$$

The immediate impact of a change in x on y is depicted by β_0.

In the models we modified the ways we estimate the explanatory variable. The two categories for the explanatory variables that we used are defined by X'_t and D'_t, for non-binary and dummy variables respectively.

We inspect the correlation between the dependent and independent variables. The correlation matrix suggests almost ideal linear relationship between the variables RPM and ASM. Therefore, I decided to estimated the models with only one dependent variable: RPM. As for the independent variables, there are no highly correlated pairs, therefore, the full set on variables is used for the models estimation.

6.1 Model I

As we mentioned above, we have several options on estimating the pandemic as an explanatory variable, and in the first model it is set as a dummy variable. The model can be less precise since it emits the factors connected with overall circumstances. Since our aim is to estimate the causal effect of COVID-19 pandemic on the performance of low-cost and full-cost U.S. carriers we have two models one for full-cost:

$$\log(\mathrm{RPM\_FC}) = \beta_0 + \beta_X X'_t + \beta_D D'_t + \beta_{\mathrm{COV-19}} D_{\mathrm{COV19}} + \beta_{\mathrm{COV-19}_{t-1}} D_{\mathrm{COV19}_{t-1}} + \varepsilon_t$$

And one for the low-cost U.S. carriers:

$$\log(\mathrm{RPM\_LC}) = \beta_0 + \beta_X X'_t + \beta_D D'_t + \beta_{\mathrm{COV-19}} D_{\mathrm{COV19}} + \beta_{\mathrm{COV-19}_{t-1}} D_{\mathrm{COV19}_{t-1}} + \varepsilon_t$$

We use log to improve the accuracy. The variable D_{COV19} is equal to 0, besides the months from March 2020, where the value is 1. $D_{\mathrm{COV19}_{t-1}}$ is equal to 0, besides the months that start from April 2020, where the value is 1.

6.2 Model II

Ito & Lee (2005a) in their research related to impact of 9/11 terrorist attacks on aviation included a variable which considers the fact that people adapt to a situation and their behavior can change. Applying it to the coronaviruses effect:

$$\mathrm{COV_{estim}} = \beta_{\mathrm{COV-19}} \mathrm{D_{COV19}} + \beta_{\mathrm{COV-19_{1/m}}} \frac{1}{\mathrm{COV19_{1/m}}}$$

The dummy variable $\mathrm{D_{COV19}}$ is 1 from April 2020. $\mathrm{COV19_{1/m}}$ counts the months after April 2020 going from April is 1, May is 2, June is 3.

Model for the full-cost U.S. carriers:

$$\log(\mathrm{RPM\_FC}) = \beta_0 + \beta_X X_t' + \beta_D D_t' + \mathrm{COV\_estim} + \varepsilon_t$$

Model for low-cost U.S. carriers:

$$\log(\mathrm{RPM\_LC}) = \beta_0 + \beta_X X_t' + \beta_D D_t' + \mathrm{COV\_estim} + \varepsilon_t$$

6.3 Model III

In the following model we have two separate dummy variables. Since the effect of virus was firstly more dramatic during April and May and later the government and people started adjusting to the circumstances. The model follows as such:

$$\mathrm{COVID_{estim}} = \beta_{\mathrm{COVID-19}_{\frac{1}{m}}} \frac{1}{\mathrm{COVID19}_{\frac{1}{m}}} + \beta_{\mathrm{COVID-shock}} \mathrm{D_{COVID\_shock}} + \beta_{\mathrm{COVID-post-shock}} \mathrm{D_{COVID_{post}-shock}}$$

Model for the full-cost U.S. carriers:

$$\log(\mathrm{RPM\_FC}) = \beta_0 + \beta_X X_t' + \beta_D D_t' + \mathrm{COVID\_estim} + \varepsilon_t$$

Model for low-cost U.S. carriers:

$$\log(\mathrm{RPM\_LC}) = \beta_0 + \beta_X X_t' + \beta_D D_t' + \mathrm{COVID\_estim} + \varepsilon_t$$

6.4 Stationarity

Since we are working with time series data, we must confirm that the time series being utilized are stationary in order to execute the majority of time-series models. If a time series' probability distribution does not change throughout the course of time, it is considered to be stationary (Pesaran, 2016). The augmented Dickey-Fuller (ADF) test is the typical method for determining stationarity for univariate time series (Dickey and Fuller, 1981). The "unit root test" is another term for the stationarity test.

7. Results and interpretation

In this section I present the estimated models described in the previous section and comment on the results.

Table 7.1 Estimation results for the model 1.

	Dependent variable:		
	log(RPM)		
	All	Full cost	Low cost
I(UNEM * log(LABOR))	-0.009***	-0.010***	-0.008***
	(0.002)	(0.002)	(0.002)
TREND	0.003***	0.002***	0.006***
	(0.001)	(0.001)	(0.001)
COVID19	-0.619***	-0.639***	-0.597***
	(0.029)	(0.029)	(0.032)
lag(COVID19)	-0.051	-0.087	-0.004
	(0.060)	(0.062)	(0.060)
CONTI	-0.178***	-0.183***	-0.183***
	(0.065)	(0.064)	(0.070)
USAirw	-0.183*	-0.196**	-0.175
	(0.096)	(0.093)	(0.109)
SARS	0.161***	0.167***	0.146***
	(0.036)	(0.036)	(0.040)
FUEL	0.001***	0.001***	0.001***
	(0.0002)	(0.0002)	(0.0002)
IRAQ	-0.059*	-0.063*	-0.048
	(0.032)	(0.032)	(0.038)
LEAP	-0.011	-0.017	0.009
	(0.089)	(0.094)	(0.080)
SEAS	0.137***	0.136***	0.132***
	(0.025)	(0.026)	(0.024)
SWINEFLU	0.296***	0.311***	0.263***
	(0.075)	(0.073)	(0.083)
Constant	25.117***	24.978***	23.126***
	(0.109)	(0.104)	(0.123)
Observations	239	239	239
R^2	0.732	0.757	0.770
Adjusted R^2	0.718	0.744	0.758
Residual Std. Error (df = 226)	0.188	0.191	0.194
F Statistic (df = 12; 226)	51.540***	58.706***	63.089***
Note:	*p**p***p<0.01		

Unemployment has negative significant effect on RPM being stronger for the full-cost carriers and weaker for the low-cost ones. Trend in low-cost carriers has a stronger impact on RPM, while seasonal effects (summer and Christmas holidays) have almost equal effect for both low-cost and full-cost carriers.

The main variable of interest, COVID19, has a significant negative immediate effect, while the lagged effect is not statistically significant. The negative effect of COVID19 on RPM of the full-cost carriers is stronger compared to the low-cost airlines.

It is interesting to see that the previous pandemics, Swine Flu and SARS both produced positive and significant effect on RPM of the U.S. Airlines.

In order to quantify the effect of COVID-19, it is possible to write how the COVID19 term affects the outcome variable RPM in the model (e.g. for all airlines):

$$\mathrm{logRPM} = \cdots - 0.619\ \mathrm{COVID19} + \cdots$$

COVID19 equals 1 for the months after March 2020 including and 0 otherwise. Therefore, in March 2020 the immediate effect of COVID19 can be written in the model as:

$$\mathrm{logRPM}_{\mathrm{Mar2020}} - \mathrm{logRPM}_{\mathrm{Feb2020}} = \log\left(\frac{\mathrm{RPM}_{\mathrm{Mar2020}}}{\mathrm{RPM}_{\mathrm{Feb2020}}}\right) = -0.619\ (1-0) = -0.6619$$

The relative change in RPM is thus derived as $\frac{\mathrm{RPM}_{\mathrm{Mar2020}}}{\mathrm{RPM}_{\mathrm{Feb2020}}} - 1 = \exp(-0.6619) - 1 = 0.5383 - 1 = -0.4617$ or 46.17% decrease.

For the full cost the average effect is -47.21% and for the low cost the effect is -44.98%. The effect for low cost is weaker.

Table 7.2 Estimation results for the model 2.

	Dependent variable:		
	log(RPM)		
	All	Full cost	Low cost
I(UNEM * log(LABOR))	-0.004***	-0.004***	-0.002***
	(0.001)	(0.001)	(0.0005)
TREND	0.002***	0.001***	0.005***
	(0.0004)	(0.0004)	(0.0004)
COVID19	-0.360***	-0.421***	-0.275***
	(0.057)	(0.063)	(0.049)
1/COVID19m	-2.748***	-2.685***	-2.923***
	(0.337)	(0.409)	(0.197)
CONTI	-0.063**	-0.071**	-0.065**
	(0.028)	(0.030)	(0.030)
USAirw	0.020	0.002	0.039
	(0.035)	(0.038)	(0.037)
SARS	0.075**	0.083**	0.058
	(0.036)	(0.035)	(0.045)
FUEL	0.001***	0.001***	0.001***
	(0.0002)	(0.0002)	(0.0001)
IRAQ	-0.087**	-0.091**	-0.074
	(0.039)	(0.037)	(0.053)
LEAP	0.027	0.021	0.050
	(0.077)	(0.082)	(0.067)
SEAS	0.132***	0.131***	0.128***
	(0.016)	(0.018)	(0.015)
SWINEFLU	0.101***	0.120***	0.054
	(0.036)	(0.038)	(0.033)
Constant	24.856***	24.725***	22.842***
	(0.034)	(0.037)	(0.034)
Observations	240	240	240
R^2	0.901	0.898	0.925
Adjusted R^2	0.895	0.892	0.921
Residual Std. Error (df = 227)	0.114	0.124	0.111
F Statistic (df = 12; 227)	171.331***	166.072***	234.222***
Note:	*p**p***p<0.01		

In this model the direction of effects for unemployment, trend and seasonality is similar to the model 1. Also SWINEFLU and SARS have the same direction but lower magnitude. For both types of airlines the immediate effect of COVID-19 is weaker. Same as in the model 1 this effect is larger for the full-cost carriers and weaker for the low-cost airlines (-42.1% versus

-27.5%). This is the effect of COVID-19 pandemics itself, controlling for all other variables, because the model controls for the possible indirect effects of COVID-19 through unemployment, fuel cost and other variables affected by the pandemics and, as a chain effect, resulted in RPM change.

In order to understand how to interpret the coefficient on $\frac{1}{\mathrm{COVID19}_{1/\mathrm{m}}}$ it is possible to write the part of the model that includes this term:

$$\mathrm{logRPM} = \cdots - 2.748\,\frac{1}{\mathrm{COVID19}_{1/\mathrm{m}}} + \cdots$$

Before March 2020 including $\frac{1}{\mathrm{COVID19}_{1/\mathrm{m}}} = 0$, in April 2020 $\frac{1}{\mathrm{COVID19}_{1/\mathrm{m}}} = \frac{1}{1}$, and in May 2020 $\frac{1}{\mathrm{COVID19}_{1/\mathrm{m}}} = \frac{1}{2}$ etc.

So, in April 2020:

$$\mathrm{logRPM}_{\mathrm{Apr2020}} - \mathrm{logRPM}_{\mathrm{Mar2020}} = \log\left(\frac{\mathrm{RPM}_{\mathrm{Apr2020}}}{\mathrm{RPM}_{\mathrm{Mar2020}}}\right) = -2.748 \times (1 - 0) = -2.748$$

And $\frac{\mathrm{RPM}_{\mathrm{Apr2020}}}{\mathrm{RPM}_{\mathrm{Mar2020}}} - 1 = \exp(-2.748) - 1 = 0.064 - 1 = -0.9359$ which corresponds to 93.59% decrease in RPM between April 2020 and March 2020.

The same calculation in May 2020 yields:

$$\mathrm{logRPM}_{\mathrm{May2020}} - \mathrm{logRPM}_{\mathrm{Mar2020}} = \log\left(\frac{\mathrm{RPM}_{\mathrm{May2020}}}{\mathrm{RPM}_{\mathrm{Mar2020}}}\right) = -2.748 \times \left(\frac{1}{2} - 0\right) = -1.3738$$

And $\frac{\mathrm{RPM}_{\mathrm{May2020}}}{\mathrm{RPM}_{\mathrm{Mar2020}}} - 1 = \exp(-1.3738) - 1 = 0.2531 - 1 = -0.7469$ which corresponds to 74.69% decrease in RPM in May 2020 compared to March 2020.

By analogy the lagged effect of COVID-19 for all airlines, full and low-cost airlines over the year after COVID-19 start (April 2020 – March 2021) is computed and displayed in the Table 7.3.

	DATE	*COVID19m*	*ALL*	*FULL*	*LOW*
211	04.01.20	1	-93,59	-93,18	-94,62
212	05.01.20	0,5	-74,69	-73,88	-76,81
213	06.01.20	0,3	-59,98	-59,14	-62,26
214	07.01.20	0,3	-49,69	-48,89	-51,85
215	08.01.20	0,2	-42,28	-41,55	-44,27
216	09.01.20	0,2	-36,74	-36,07	-38,56
217	10.01.20	0,1	-32,46	-31,86	-34,14
218	11.01.20	0,1	-29,07	-28,51	-30,61
219	12.01.20	0,1	-26,31	-25,79	-27,73
220	01.01.21	0,1	-24,02	-23,55	-25,35
221	02.01.21	0,1	-22,1	-21,66	-23,34
222	03.01.21	0,1	-20,46	-20,05	-21,62

Table 7.3 Lagged effect of COVID-19 for all airlines

While the immediate effect of COVID-19 was stronger for the full-cost carriers, the delayed effects computed in table 7.3 are stronger for the low-cost airlines. This suggest that the full-cost airlines have recovered faster after the pandemics start, while the low-cost companies needed more time and the delayed effect of the COVID-19 was more pronounced.

Table 7.4 Estimation results for the model 3.

	Dependent variable:		
	log(RPM)		
	All	Full cost	Low cost
I(UNEM * log(LABOR))	-0.003***	-0.004***	-0.002***
	(0.001)	(0.001)	(0.0005)
TREND	0.001***	0.001	0.004***
	(0.0005)	(0.0005)	(0.0005)
1/COVID19m	-3.094***	-3.208***	-2.910***
	(0.655)	(0.816)	(0.348)
COVID19shock	-0.054	0.050	-0.302
	(0.518)	(0.646)	(0.272)
COVID19post	-0.304***	-0.353***	-0.244***
	(0.076)	(0.088)	(0.055)
CONTI	-0.044	-0.050	-0.046
	(0.033)	(0.035)	(0.034)
USAirw	0.030	0.012	0.049
	(0.038)	(0.040)	(0.040)
SARS	0.065*	0.071*	0.051
	(0.039)	(0.038)	(0.048)
FUEL	0.001***	0.001***	0.001***
	(0.0002)	(0.0002)	(0.0002)
IRAQ	-0.089**	-0.092**	-0.078
	(0.042)	(0.040)	(0.055)
LEAP	0.033	0.027	0.055
	(0.075)	(0.079)	(0.065)
SEAS	0.136***	0.137***	0.129***
	(0.016)	(0.017)	(0.015)
SWINEFLU	0.101***	0.119***	0.058*
	(0.038)	(0.041)	(0.034)
Constant	24.853***	24.721***	22.840***
	(0.035)	(0.038)	(0.035)
Observations	240	240	240
R^2	0.892	0.890	0.919
Adjusted R^2	0.885	0.884	0.914
Residual Std. Error (df = 226)	0.120	0.129	0.116
F Statistic (df = 13; 226)	143.144***	140.627***	197.618***
Note:	*p**p***p<0.01		

The most interesting difference of these estimated effects is not significant effect of the COVID19shock variable. Practically this means that COVID-19 itself in April and May 2020 has not affected RPM. Clearly, COVID-19 affected other covariates and thus had indirect effect on RPM. But the post-shock effect is statistically significant and has a negative sign. Starting from June 2020 COVID-19 pandemics itself became a negative factor for RPM of the U.S. carriers being stronger for the full-cost airlines and weaker for the low-cost ones.

After the models estimation I performed the model diagnostics with the help of Shapiro-Wilk, Breusch-Pagan and Breusch-Godfrey tests.

Table 7. 5 Model diagnostics for all U.S. airlines

	Model 1 all airlines	*Model 2 all airlines*	*Model 3 all airlines*
Shapiro-Wilk test statistic	0.883	0.984	0.953
Shapiro-Wilk test p-value	0	0.01	0
Shapiro-Wilk test decision	$p < 0.05$, Not normal	$p < 0.05$, Not normal	$p < 0.05$, Not normal
Breusch-Pagan test statistic	71.368	120.261	72.603
Breusch-Pagan test p-value	0	0	0
Breusch-Pagan test decision	$p < 0.05$, Heteroskedastic	$p < 0.05$, Heteroskedastic	$p < 0.05$, Heteroskedastic
Breusch-Godfrey test statistic	114.47	77.035	65.227
Breusch-Godfrey test p-value	0	0	0
Breusch-Godfrey test decision	$p < 0.05$, Correlated	$p < 0.05$, Correlated	$p < 0.05$, Correlated

Table 7. 6 Model diagnostics for U.S. full-cost airlines

	Model 1 full cost	***Model 2 full cost***	***Model 3 full cost***
Shapiro-Wilk test statistic	0.915	0.98	0.953
Shapiro-Wilk test p-value	0	0.002	0
Shapiro-Wilk test decision	$p < 0.05$, Not normal	$p < 0.05$, Not normal	$p < 0.05$, Not normal
Breusch-Pagan test statistic	81.241	140.664	97.166
Breusch-Pagan test p-value	0	0	0
Breusch-Pagan test decision	$p < 0.05$, Heteroskedastic	$p < 0.05$, Heteroskedastic	$p < 0.05$, Heteroskedastic
Breusch-Godfrey test statistic	127.129	86.206	70.214
Breusch-Godfrey test p-value	0	0	0
Breusch-Godfrey test decision	$p < 0.05$, Correlated	$p < 0.05$, Correlated	$p < 0.05$, Correlated

Table 7. 7 Model diagnostics for U.S. low-cost airlines

	Model 1 low cost	***Model 2 low cost***	***Model 3 low cost***
Shapiro-Wilk test statistic	0.812	0.99	0.966
Shapiro-Wilk test p-value	0	0.09	0
Shapiro-Wilk test decision	$p < 0.05$, Not normal	$p > 0.05$, Normal	$p < 0.05$, Not normal
Breusch-Pagan test statistic	60.746	87.177	42.47
Breusch-Pagan test p-value	0	0	0
Breusch-Pagan test decision	$p < 0.05$, Heteroskedastic	$p < 0.05$, Heteroskedastic	$p < 0.05$, Heteroskedastic
Breusch-Godfrey test statistic	86.885	66.134	66.266
Breusch-Godfrey test p-value	0	0	0
Breusch-Godfrey test decision	$p < 0.05$, Correlated	$p < 0.05$, Correlated	$p < 0.05$, Correlated

For the most of the models the tests suggest that the errors are not normally distributed, heteroskedastic and serially correlated.

The fact that the errors are not normally distributed partially alleviated with the size of the dataset (239 observations) which suggests that their asymptotic distribution is the normal one.

Heteroskedasticity of the residuals in all models is solved using heteroskedasticity robust standard errors. The estimation results for the models 1-3 are reported with the robust standard errors.

Finally, the serial correlation of the residuals appears because of the time-series nature of the dependent variable RPM. A possible solution for this would be the estimation of the ARIMA class models.

8. Conclusion

The purpose of the following thesis was to analyze the COVID-19 impact on U.S. airline market. The key was to separately estimate the models for full-cost and low-cost airlines and thus determine if the impact of the virus on the two airline categories was consistent.

The available literature suggests that for European and U.S. market low-cost carriers have suffered fewer financial losses. Specifically, Fontanet-Pérez, Vázquez and Carou (2022) based their study on 10 U.S. low-cost and full-cost airlines, utilizing variables such as RPM, ASM, and the number of operated flights but only calculated the descriptive statistics. Additionally, their chosen time frame included data from 2015 to 2020. Thus, the added value of this thesis is extending the research by estimating several OLS regression models for all U.S. airlines, then individually for low-cost and full-cost airlines for time frame 2002-10-01 to 2022-09-01. To our knowledge, such analysis has not been conducted for the U.S. market.

The first model, where COVID-19 is set as a dummy-variable with a one-month lag, reveals that it had a significant negative immediate effect on all the airlines. However, the negative effect of COVID-19 variable on RPM of full-cost carriers shows average of -47.21%, meanwhile shows lower negative effect of -44,98% for low-cost airlines. The lagged effect is not statistically significant. We also previously highlighted that we took into account several binary control variables since they could influence RPM as an outcome variable. The interesting observation was that the Swine Flu and SARS had produced positive significant effect on RPM of the U.S. airlines. In the second model, COVID-19 is a dummy-variable and we take into account adaptation variable. For both types of airlines the immediate effect of COVID-19 is weaker. Same as in the model 1 this effect is larger for the full-cost carriers and weaker for the low-cost airlines (-42.1% versus -27.5%). This is the effect of COVID-19 pandemics itself, controlling for all other variables, because the model controls for the possible indirect effects of COVID-19 through unemployment, fuel cost and other variables affected by the pandemics and, as a chain effect, resulted in RPM change. The calculation of the lagged effect of COVID-19 for all airlines, full and low-cost airlines over the year after COVID-19 start (April 2020 – March 2021), showed that the delayed effects computed in table 7.3 are stronger for the low-cost airlines. This suggest that the full-cost airlines have recovered faster after the pandemics start, while the low-cost companies needed more time and the delayed effect of the COVID-19 was more pronounced.

Finally, the third model where we have the dummy and adaptation variable separated to shock and post-shock. It showed that COVID-19 itself in April and May 2020 has not affected RPM. Clearly, COVID-19 affected other covariates and thus had indirect effect on RPM. But the post-shock effect is statistically significant and has a negative sign. Starting from June 2020 COVID-19 pandemics itself became a negative factor for RPM of the U.S. carriers being stronger for the full-cost airlines and weaker for the low-cost ones. We also conducted a model diagnostic and the results showed that the errors are not typically distributed for the majority of the models. The size of the dataset (239 observations) substantially mitigates the errors' non-normal distribution, suggesting that their asymptotic distribution is normal one.

The findings of this thesis can be found useful not only for investigating the impacts of shocks on the airline industry, but it can also be used to expand our understanding of how events might influence full-cost and low-cost airlines in various ways. There is also another business model of airline companies which is ultra low-cost (even-though not many), adding it to the research is also a possible extension of the following work. For further papers, it would be interesting the observe the results for other countries.

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Appendix A: Figures

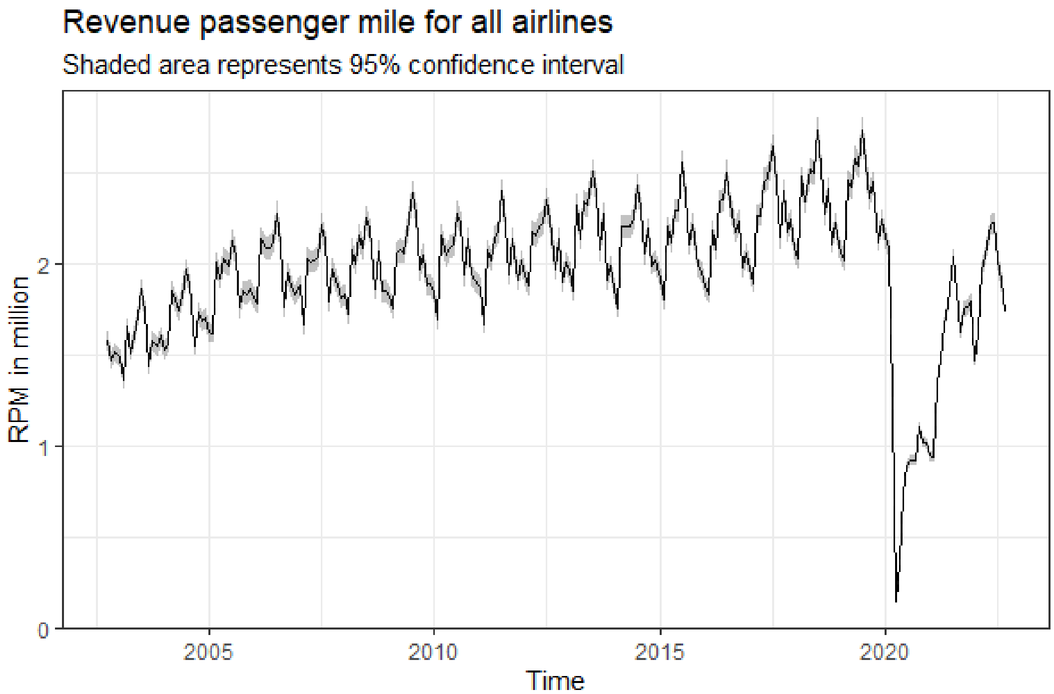

Figure 5.1. Revenue per mile dynamics for the U.S. Carriers

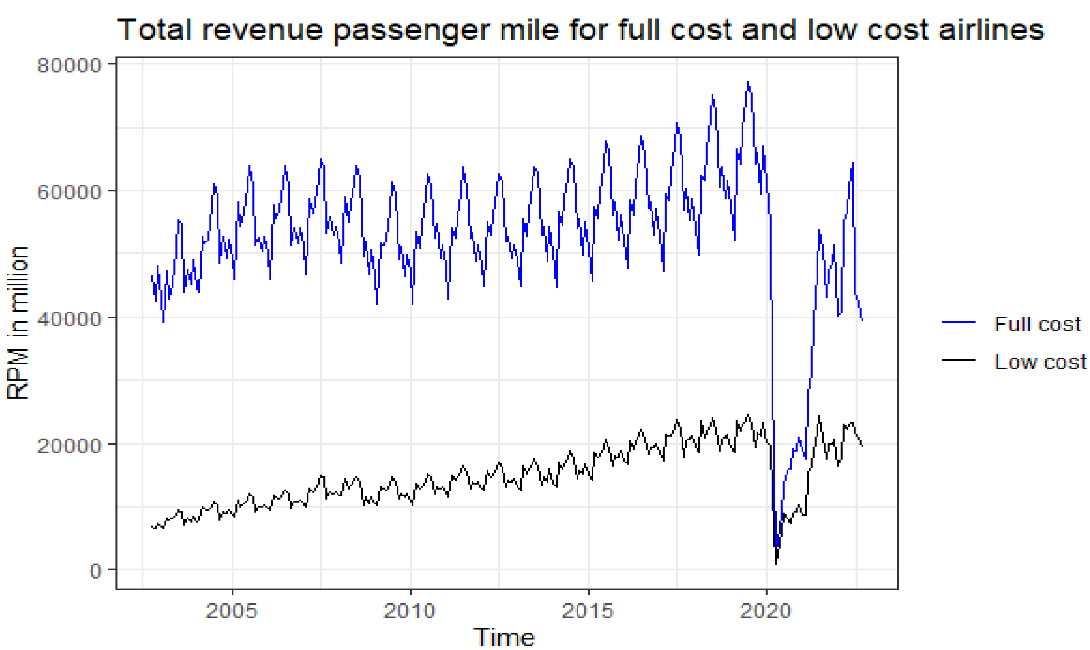

Figure 5.2. Revenue per mile dynamics for U.S. low-cost and full-service Carriers

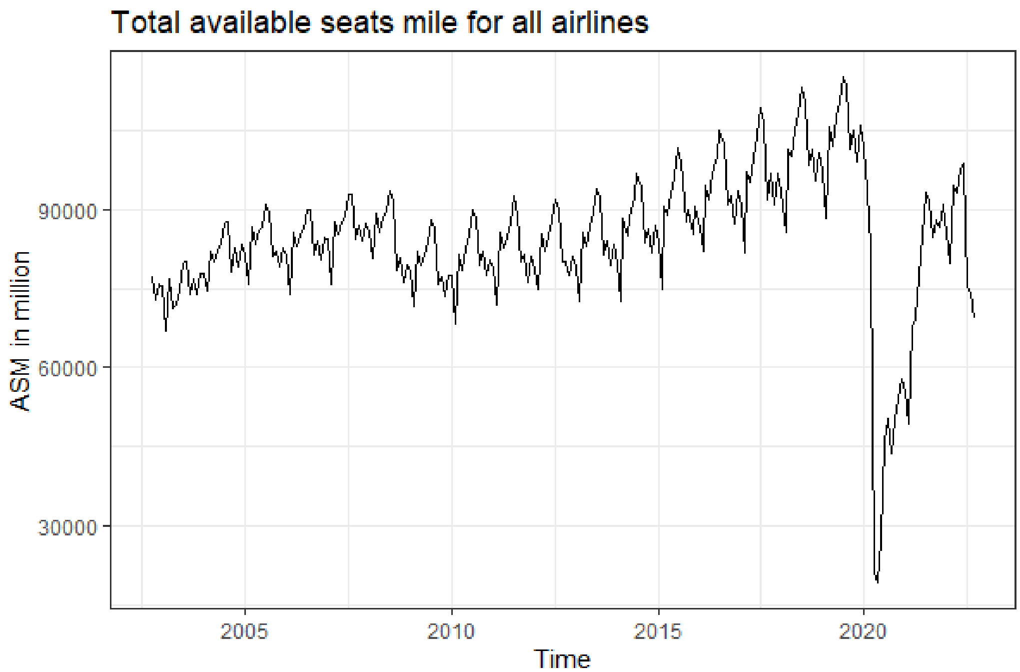

Figure 5.3. Available seats mile dynamics for the U.S. Carriers

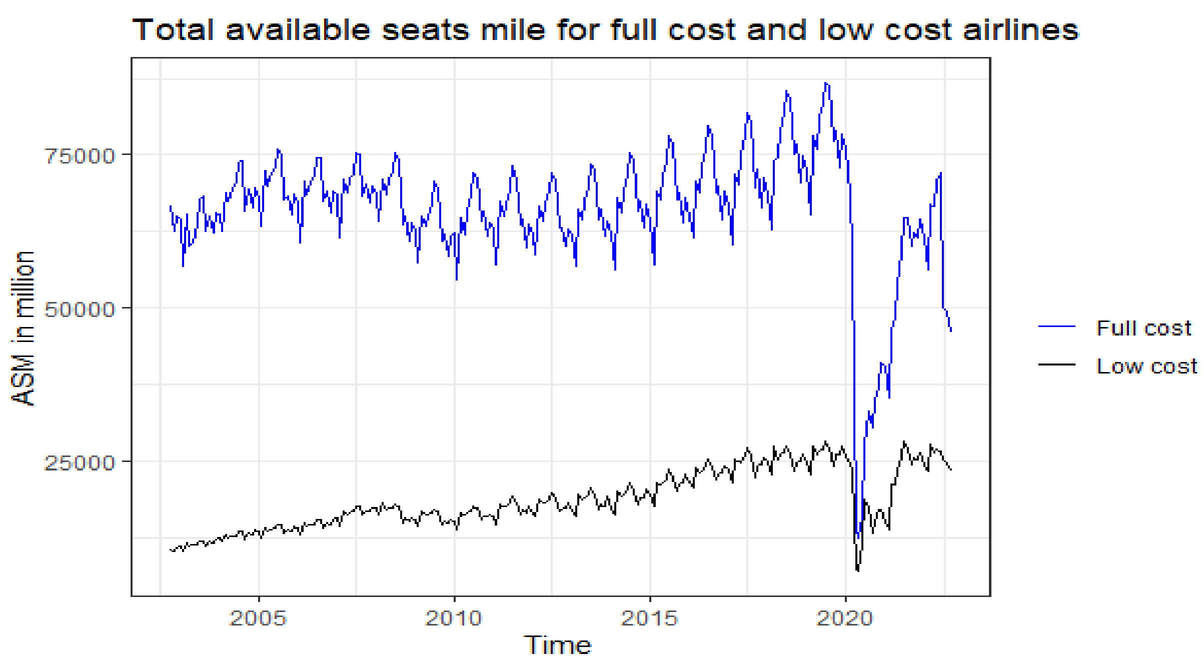

Figure 5.4. Available seats mile dynamics for the U.S. low-cost and full-cost carriers

Appendix B: Tables

PERIOD	*Mean*	*SD*	*Min*	*10%*	*25%*	*50%*	*75%*	*90%*	*Max*
2002/10-2007/12	1,698,061	5,658,280	0	0	0	37,278	810,568	3,915,886	156,885,358
2008/01-2012/12	1,900,273	6,083,478	0	0	124	69,641	926,786	4,296,770	172,828,758
2013/01-2017/12	1,991,316	6,259,650	0	0	140	86,362	1,020,924	4,652,478	193,903,740
2018/01-2022/09	1,811,402	5,635,919	0	0	0	69,580	1,012,176	4,365,348	157,671,500

Table 5.1. Summary statistics on Revenue per mile for low-cost U.S. Carriers

PERIOD	*Mean*	*SD*	*Min*	*10%*	*25%*	*50%*	*75%*	*90%*	*Max*
2002/10-2007/12	2,925,435	4,911,156	0	34,606	190,380	1,340,384	3,793,861	7,336,867	89,962,640
2008/01-2012/12	2,962,939	4,517,317	0	49,104	221,746	1,436,484	3,839,435	7,470,690	61,944,300
2013/01-2017/12	3,162,284	4,647,165	0	90,637	335,340	1,568,298	4,288,024	7,987,738	104,962,275
2018/01-2022/09	2,323,386	3,829,548	0	71,709	235,080	943,452	2,922,908	6,269,431	124,945,425

Table 5.2. Summary statistics on Revenue per mile for full-cost U.S. Carriers

PERIOD	*Mean*	*SD*	*Min*	*10%*	*25%*	*50%*	*75%*	*90%*	*Max*
2002/10-2007/12	2,190,019	6,897,781	0	0	346	73,800	1,178,200	5,269,316	162,438,822
2008/01-2012/12	2,327,082	7,202,271	0	0	1,062	114,750	1,242,000	5,372,136	215,391,816
2013/01-2017/12	2,394,940	7,378,198	0	0	1,428	133,200	1,286,208	5,610,405	209,855,475
2018/01-2022/09	2,313,089	6,875,094	0	0	1,035	127,800	1,379,040	5,698,560	176,168,000

Table 5.3. Summary statistics on Available seats mile for low-cost U.S. Carriers

PERIOD	*Mean*	*SD*	*Min*	*10%*	*25%*	*50%*	*75%*	*90%*	*Max*
2002/10-2007/12	3,985,590	6,073,341	0	78,638	279,851	2,054,178	5,423,282	9,839,232	95,365,920
2008/01-2012/12	3,722,307	5,374,369	0	83,590	302,760	1,912,800	4,979,128	9,354,012	75,432,474
2013/01-2017/12	3,781,554	5,345,628	0	1E+05	434,012	1,965,814	5,208,000	9,418,479	123,601,500
2018/01-2022/09	2,972,809	4,599,073	0	1E+05	353,850	1,310,400	3,852,744	7,857,144	152,460,000

Table 5.4. Summary statistics on Available seats mile for full-cost U.S. Carriers

Table 7.1 Estimation results for the model 1.

	Dependent variable:		
	log(RPM)		
	All	Full cost	Low cost
I(UNEM * log(LABOR))	-0.009***	-0.010***	-0.008***
	(0.002)	(0.002)	(0.002)
TREND	0.003***	0.002***	0.006***
	(0.001)	(0.001)	(0.001)
COVID19	-0.619***	-0.639***	-0.597***
	(0.029)	(0.029)	(0.032)
lag(COVID19)	-0.051	-0.087	-0.004
	(0.060)	(0.062)	(0.060)
CONTI	-0.178***	-0.183***	-0.183***
	(0.065)	(0.064)	(0.070)
USAirw	-0.183*	-0.196**	-0.175
	(0.096)	(0.093)	(0.109)
SARS	0.161***	0.167***	0.146***
	(0.036)	(0.036)	(0.040)
FUEL	0.001***	0.001***	0.001***
	(0.0002)	(0.0002)	(0.0002)
IRAQ	-0.059*	-0.063*	-0.048
	(0.032)	(0.032)	(0.038)
LEAP	-0.011	-0.017	0.009
	(0.089)	(0.094)	(0.080)
SEAS	0.137***	0.136***	0.132***
	(0.025)	(0.026)	(0.024)
SWINEFLU	0.296***	0.311***	0.263***
	(0.075)	(0.073)	(0.083)
Constant	25.117***	24.978***	23.126***
	(0.109)	(0.104)	(0.123)
Observations	239	239	239
R^2	0.732	0.757	0.770
Adjusted R^2	0.718	0.744	0.758
Residual Std. Error (df = 226)	0.188	0.191	0.194
F Statistic (df = 12; 226)	51.540***	58.706***	63.089***
Note:	*p**p***p<0.01		

Table 7.2 Estimation results for the model 2.

	Dependent variable:		
	log(RPM)		
	All	Full cost	Low cost
I(UNEM * log(LABOR))	-0.004***	-0.004***	-0.002***
	(0.001)	(0.001)	(0.0005)
TREND	0.002***	0.001***	0.005***
	(0.0004)	(0.0004)	(0.0004)
COVID19	-0.360***	-0.421***	-0.275***
	(0.057)	(0.063)	(0.049)
1/COVID19m	-2.748***	-2.685***	-2.923***
	(0.337)	(0.409)	(0.197)
CONTI	-0.063**	-0.071**	-0.065**
	(0.028)	(0.030)	(0.030)
USAirw	0.020	0.002	0.039
	(0.035)	(0.038)	(0.037)
SARS	0.075**	0.083**	0.058
	(0.036)	(0.035)	(0.045)
FUEL	0.001***	0.001***	0.001***
	(0.0002)	(0.0002)	(0.0001)
IRAQ	-0.087**	-0.091**	-0.074
	(0.039)	(0.037)	(0.053)
LEAP	0.027	0.021	0.050
	(0.077)	(0.082)	(0.067)
SEAS	0.132***	0.131***	0.128***
	(0.016)	(0.018)	(0.015)
SWINEFLU	0.101***	0.120***	0.054
	(0.036)	(0.038)	(0.033)
Constant	24.856***	24.725***	22.842***
	(0.034)	(0.037)	(0.034)
Observations	240	240	240
R^2	0.901	0.898	0.925
Adjusted R^2	0.895	0.892	0.921
Residual Std. Error (df = 227)	0.114	0.124	0.111
F Statistic (df = 12; 227)	171.331***	166.072***	234.222***
Note:	*p**p***p<0.01		

	DATE	*COVID19m*	*ALL*	*FULL*	*LOW*
211	04.01.20	1	-93,59	-93,18	-94,62
212	05.01.20	0,5	-74,69	-73,88	-76,81
213	06.01.20	0,3	-59,98	-59,14	-62,26
214	07.01.20	0,3	-49,69	-48,89	-51,85
215	08.01.20	0,2	-42,28	-41,55	-44,27
216	09.01.20	0,2	-36,74	-36,07	-38,56
217	10.01.20	0,1	-32,46	-31,86	-34,14
218	11.01.20	0,1	-29,07	-28,51	-30,61
219	12.01.20	0,1	-26,31	-25,79	-27,73
220	01.01.21	0,1	-24,02	-23,55	-25,35
221	02.01.21	0,1	-22,1	-21,66	-23,34
222	03.01.21	0,1	-20,46	-20,05	-21,62

Table 7.3 Lagged effect of COVID-19 for all airlines

Table 7.4 Estimation results for the model 3.

	Dependent variable:		
	log(RPM)		
	All	Full cost	Low cost
I(UNEM * log(LABOR))	-0.003***	-0.004***	-0.002***
	(0.001)	(0.001)	(0.0005)
TREND	0.001***	0.001	0.004***
	(0.0005)	(0.0005)	(0.0005)
1/COVID19m	-3.094***	-3.208***	-2.910***
	(0.655)	(0.816)	(0.348)
COVID19shock	-0.054	0.050	-0.302
	(0.518)	(0.646)	(0.272)
COVID19post	-0.304***	-0.353***	-0.244***
	(0.076)	(0.088)	(0.055)
CONTI	-0.044	-0.050	-0.046
	(0.033)	(0.035)	(0.034)
USAirw	0.030	0.012	0.049
	(0.038)	(0.040)	(0.040)
SARS	0.065*	0.071*	0.051
	(0.039)	(0.038)	(0.048)
FUEL	0.001***	0.001***	0.001***
	(0.0002)	(0.0002)	(0.0002)
IRAQ	-0.089**	-0.092**	-0.078
	(0.042)	(0.040)	(0.055)
LEAP	0.033	0.027	0.055
	(0.075)	(0.079)	(0.065)
SEAS	0.136***	0.137***	0.129***
	(0.016)	(0.017)	(0.015)
SWINEFLU	0.101***	0.119***	0.058*
	(0.038)	(0.041)	(0.034)
Constant	24.853***	24.721***	22.840***
	(0.035)	(0.038)	(0.035)
Observations	240	240	240
R^2	0.892	0.890	0.919
Adjusted R^2	0.885	0.884	0.914
Residual Std. Error (df = 226)	0.120	0.129	0.116
F Statistic (df = 13; 226)	143.144***	140.627***	197.618***
Note:	*p**p***p<0.01		

Table 7. 5 Model diagnostics for all U.S. airlines

	Model 1 all airlines	*Model 2 all airlines*	*Model 3 all airlines*
Shapiro-Wilk test statistic	0.883	0.984	0.953
Shapiro-Wilk test p-value	0	0.01	0
Shapiro-Wilk test decision	p < 0.05, Not normal	p < 0.05, Not normal	p < 0.05, Not normal
Breusch-Pagan test statistic	71.368	120.261	72.603
Breusch-Pagan test p-value	0	0	0
Breusch-Pagan test decision	p < 0.05, Heteroskedastic	p < 0.05, Heteroskedastic	p < 0.05, Heteroskedastic
Breusch-Godfrey test statistic	114.47	77.035	65.227
Breusch-Godfrey test p-value	0	0	0
Breusch-Godfrey test decision	p < 0.05, Correlated	p < 0.05, Correlated	p < 0.05, Correlated

Table 7. 6 Model diagnostics for U.S. full-cost airlines

	Model 1 full cost	*Model 2 full cost*	*Model 3 full cost*
Shapiro-Wilk test statistic	0.915	0.98	0.953
Shapiro-Wilk test p-value	0	0.002	0
Shapiro-Wilk test decision	p < 0.05, Not normal	p < 0.05, Not normal	p < 0.05, Not normal
Breusch-Pagan test statistic	81.241	140.664	97.166
Breusch-Pagan test p-value	0	0	0
Breusch-Pagan test decision	p < 0.05, Heteroskedastic	p < 0.05, Heteroskedastic	p < 0.05, Heteroskedastic
Breusch-Godfrey test statistic	127.129	86.206	70.214
Breusch-Godfrey test p-value	0	0	0
Breusch-Godfrey test decision	p < 0.05, Correlated	p < 0.05, Correlated	p < 0.05, Correlated

Table 7. 7 Model diagnostics for U.S. low-cost airlines

	Model 1 low cost	***Model 2 low cost***	***Model 3 low cost***
Shapiro-Wilk test statistic	0.812	0.99	0.966
Shapiro-Wilk test p-value	0	0.09	0
Shapiro-Wilk test decision	p < 0.05, Not normal	p > 0.05, Normal	p < 0.05, Not normal
Breusch-Pagan test statistic	60.746	87.177	42.47
Breusch-Pagan test p-value	0	0	0
Breusch-Pagan test decision	p < 0.05, Heteroskedastic	p < 0.05, Heteroskedastic	p < 0.05, Heteroskedastic
Breusch-Godfrey test statistic	86.885	66.134	66.266
Breusch-Godfrey test p-value	0	0	0
Breusch-Godfrey test decision	p < 0.05, Correlated	p < 0.05, Correlated	p < 0.05, Correlated