RECOVERY PERIOD OF AIR TRANSPORTATION: A FORECAST WITH VECTOR ERROR CORRECTION MODEL

Tüzün Tolga İnan
•
Bahcesehir University
tuzuntolga.inan@sad.bau.edu.tr

Abstract

Air transport is the primary module of civil aviation and because of its nature, air transport has been simultaneously affected by Pandemics and crises. The influence of COVID-19 was more devastating than the other Pandemics and crises due to its global effect. This effect has continued a long period that still this effect exists now with a slight trend. The aim of this study is to analyse the selected variables that shows the past and future trend of air transportation related to operational and financial status. These variables are the primary ones that can define the countries' general status in air transport. The forecasting results are examined by 9-months forecasting with Vector Error Correction Model. It is forecasted that slightly decreasing trend will proceed in the following 9-months for passenger transportation due to fall and winter seasons. It is forecasted that slightly upward trend will proceed in the following 3-months and slightly decreased in the other 6-months for cargo transportation due to potential economic crisis in 2023. The originality of this paper is the first research related to analyse passenger and freight transportation together with the operational and financial parameters that defined in the sample of data and methodology sections.

Keywords: passenger load factor, cargo load factor, vector error correction model, air transportation, recovery period.

1. Introduction

Air transportation is a staminal facilitator for the countries' development. Air transportation includes air passenger and air freight modules. Especially air passenger module is related to the economic status and welfare of people. Trade and tourism primarily affect the country's development rates, so the development of air passenger transportation increases revenues with the development interest of demanded services in high amounts [1]. This study forecasts the following three quarters (9-month period) to analyse the negative impact of COVID-19 on air transportation. When time passes and the COVID-19 effect has decreased, air passenger demand will probably rise, and the growing trend of civil aviation will rise too. Nearly all countries prohibited travel to other countries because of the increment in COVID-19 cases. Several strategies regarding restrictions and procedures have been applied in countries, so air passenger traffic numbers decreased [2]. Before COVID-19 emerged, the annual development rate of the civil aviation industry in 21st century has 4.2%. More than 5000 airlines and 40 million flights clearly show that the global airline market value is measured by billions of dollars (USD). Furthermore, civil aviation affects the Gross Domestic Product (GDP) by more than 1% globally [3]. So, the importance of civil aviation is better than the other transportation modules. Nowadays, there have more than 1200 big-scale international airports globally and these airports provide the transportation of more than 4 billion passengers annually [4].

Besides air passenger, air freight is described as the transportation process of products by using an air carrier. Air freight is evaluated as an important transportation module when these goods are carried globally [5]. Air transportation has a significant development trend globally, so the revenues and populations have increased with the alteration of industrial structure. This status has affected the progress of free trade which enhanced this development trend globally [6]. With the development of air freight transportation demand, air traffic models have also altered and turned into a more complicated structure [7]. The profit level of this transportation module reached 40% in 2009, while this profit was only 5% in 2000 [8, 9]. In 2014, Boeing Company [10] forecasted that the air freight industry has proceeded to develop by a 4.7% per year. The forecasts show that this number will triple its income in 2033. The estimations specified that from 2013 to 2033, the billion ton-kilometers (RTKs) have risen from 207.8 to 521.8. There have several strategies for the sustainability of the stunning development of expanding international trade [11, 12]. So, airlines take place in the operation process of air freight. They enhance their strategic plans to reflect changes in the global competitive landscape [9; 13]. Thus, increasing theoretical researches have tried to solve the difficulties in the operational process in air freight since the 1990s [14]. Besides, there was a general supposition about the global aviation industry with an improvement trend in 2020. So, the status was the same as the growing years that has in a consecutive growth in air passenger, freight, and incomes in the latest years. Following this developing pattern, several airlines have made investments in purchasing and leasing more aircraft from well-known manufacturers like Airbus and Boeing, offering significant savings on new orders with long-term contracts [15].

In addition to these definitions related to air passenger and air freight transport, this study aims to analyze the 11 variables that mentioned below according to all active countries. These variables are;

- Gross Domestic Product (GDP),
- Total National Air Passenger Numbers,
- Total International Air Passenger Numbers,
- Total National Air Freight Numbers.
- Total International Air Freight Numbers
- Available Seat Kilometer for Air Passenger Transportation
- Revenue per Passenger Kilometer for Air Passenger Transportation
- Passenger Load Factor for Air Passenger Transportation
- Total Available Cargo Tonne Kilometer for Air Freight Transportation
- Revenue per Cargo Tonne Kilometer for Air Freight Transportation
- Cargo Load Factor for Air Freight Transportation

In this study, these 11 variables are gathered to figure out significant factors that define the operational and financial level of air transport (passenger and freight) for countries. This study also analyses the COVID-19 effect on air passengers and air freight transport (not affected as passenger transportation) as an unprecedented worldwide crisis globally.

2. Literature Review

When it is examined the related studies, first study is related to predict the relationship between the degree of economic shocks and the temporal recovery of the global air transport business was published by Gudmundson et al. [16]. According to this study's results, the global flight demand, particularly for passengers, will take at least 2.4 years (recovery by the end of 2022) to reach pre-

COVID-19 levels. The most optimistic forecast for the recovery has continued approximately two years (recovery by the third quarter of 2022), while the most pessimistic forecast for the recovery has continued approximately for six years (recovery in 2026). According to the methodology related to passenger and freight transportation, the recovery period forecast calculated by using a univariate approach called ARIMAX. This study was published at the beginning of 2021, so the recovery is not reflecting the up-to-date data at. Second study is related to air travel was released by Truong [17]. Truong analyzed the quantity of both domestic and foreign flights. This study specified that although the number of flights during the pandemic may not have reached 2019 levels, in 2022, the number of flights will not far away about the demand for travel in 2019. In that research, neural network models for estimating domestic and international air transportation in the medium and long terms were developed and tested. To estimate passenger demand, economic factors following COVID-19 that placed restrictions on transportation were examined. In the third study, Wang and Gao [18] analyzed 87 research about air transportation. They took these studies between 2010 to 2020. They used preliminary analytical techniques to analyze the input data. In the input data, three analyses were created and collected. This analysis revealed the relationship between the reviewed studies by forecasting airlines' socioeconomic and operational characteristics in time series modelling, the study reviewed air transportation demand on international scale.

In the fourth study, Dube et al. [19] specified that because of air travel is in full swing, general problems will not resolve right away. He proposed to aviation specialists that safeguarding passengers' health and safety, planning ticket prices, boosting efficiency, ensuring high-quality in-flight amenities, and maintaining such safeguards is likewise essential for the development of air traffic. In the fifth study, Li et al. [20] specified that there was a sharp drop in passenger air travel because of COVID-19 for two reasons. These are the breakdown of demand and supply of restrictions. The study segmented passengers according to their characteristics by applying several simulations and predictions of demand for each segment. In the sixth study, Zhang et al. [21] determined econometric and subjective models related to patterns of Hong Kong's tourism revival. These models described how the COVID-19 Pandemic affected Hong Kong's tourism industry economically. They also analyzed the airline revenues due to COVID-19 effect. In the seventh and last study, Xuan et al. [22] forecasted the air transport recovery period. He used the vector autoregression approach to calculate the period of recovery. The results showed that the decisive factors of the recovery are gross domestic product (GDP) and air freight traffic.

If such a Pandemic had not happened, there was a general supposition in the worldwide aviation industry to anticipate an increasing development trend in 2020. This status was the same as the consecutive growing years for air passenger and freight transportation. The forecast reports have shown this trend for airlines about the investments in buying new aircraft from widely known aircraft manufacturers such as Airbus and Boeing by directing new order deliveries. In addition to the manufacturing companies in civil aviation, the connection between the tourism and transportation sectors has broadly been debated academically. This debate is commonly focused on air transportation. Despite the existence of other modules in transportation such as railway, maritime, road vehicles, etc., tourism issue is the most decisive one for air transportation. Correspondingly, tourism is the preferential factor for the development of air transportation and the increment of GDP related to the economic level of countries [23, 24].

Civil aviation has turned into the most important one among the other industries in its contribution to worldwide economic development. However, the development and continuation of COVID-19 will cause economic issues related to excessive tourism costs on a global scale. Correspondingly, the implementation of measures is also about the operation process planning in a global fleet of narrow and wide-body aircraft [25]. International tourism, which stands on air transportation with a ratio of (58%) for arriving passengers to countries, has reached a standstill with important ratios of negative outcomes for tourism-linked activities and numbers of employment [26]. The necessity for the airlines related to stopping their flight operations has negatively affected the demand of passengers, so the airlines do not have enough options in the usage of airports for the sustainability of the flight planning strategy rather than to use aircraft for cargo flights. Besides, these selections are required to assist the airports and airlines by ensuring a particular field for using new aircraft parking positions. The crisis in the civil aviation industry is related to interminable, connected, and unresolved problems designated for the worldwide air transportation framework [27].

When benchmarking air passenger and freight transportation, air freight is more complicated than passenger transportation because this transportation process includes more strategies and more detailed processes. When compare with passenger transportation, a compound of weight and volume, various types of services, combinations, and network planning design are more detailed. The obvious differences between freight and passenger operations demonstrate that the multidisciplinary nature of freight transportation is more complicated than passenger transportation [28, 29, 11, 30]. In general, air freight transportation has higher ambiguity than passenger transportation because of its volume capacity. In passenger transportation passengers may cancel bookings, so the passengers that do not come to the aircraft have no place on the passenger list. Because of this, International Civil Aviation Organization (ICAO) permits airlines for selling tickets at more than %10 of their capacity. The booking capacity of air freight transportation is related to the freight forwarders' planning, and it can be assigned to the volume of cargo capacity. The cargo capacity volume plans the determined flights for six or twelve months [31]. The planning of the number of goods shipped with on-time performance is more important rather than booked reservations. These reservations compose elevated fluctuations due to the management of capacity. This situation shows freight forwarders generally do not require to give the price for unserviceable freights. Without punishment charges for unserviceable freights, the forwarder can fulfil the need to reduce risks to compete with the other companies. This status actualizes with several reservations in air freight that have been planned, reserved, and cancelled after the plan because cancelled flights are not an expense for the airlines. Consequently, the reservation process can show substantial volatility in air freight more than air passenger transportation [32].

It is more challenging to predict air freight capacity than air passenger capacity. Passenger aircraft capacity is related to its total seats, but freight capacity relies on the types and volume of containers and pallets named unit load devices (ULDs). The main problems with ULDs include variety of issues such as, pivot weight, volume, type of the product, and center of gravity [29]. For example, capacity has a connection with volume, and solely weight is not a determining factor. The basic specifications of air freight include complicated decision-making models for the management of air freight capacity. Transfer routes between the origin and destination (OD) pair are significant for air freight transportation. They serve the airline for passenger transportation. Generally, big-scale airlines known as full-service carriers control the process of alleged hub-and-spoke networks. Freight and passengers are carried from diversified origins to several hubs where freight and passengers are unified and afterward carry to other hubs for using wide-body aircraft. Passenger transportation can have a problem with inadmissible passengers. These passengers cannot embark to the aircraft due to the prohibitions. In air freight transportation, the freights can transfer via numerous midpoint airports such as origin point to destination point with a quick delivery time [31].

Airlines report the origin, stopover (transit), and destination airports for both passenger and freight traffic to build the transfer route plans. These processes cover network capacity usage and have a connection between conceptual and empirical modelling. These models have an increasing trend aiming to analyse quantitative decision methods related to the operational process especially for air freight [14]. Furthermore, the literature review covers the information about air transportation with defining the decreasing trend about all active countries because of COVID-19. Also, the literature review shows the decreasing and increasing trend of air transportation numbers by making a forecast (for passenger and freight) before and after the COVID-19 Pandemic.

3. Sample of Data

For the 11 selected variables in this study, time series modeling was applied. The primary thing that affects air transportation statistics is gross domestic product (GDP). All finished products and services produced within the country for a particular period (often one year) are included in the GDP [33]. Additionally, the Federal Reserve Bank of St. Louis provided the GDP data [34] The study's introduction and literature review sections both include descriptions of air passenger and freight transportation that indicate both the domestic and international numbers involved.

The six airline variables that are still in effect are: available passenger kilometers (ASK), revenue passenger kilometers (RPK), passenger load factor for air passenger transportation (PLF), available tonne kilometers (ATK), revenue tonne kilometers (RTK), and cargo load factor (CLF) for air freight transportation. All selected variables are used for the time series modeling analysis between January 2016 and August 2022 due to the availability of data.

First, RPK and the airline's total kilometer passenger capacity are connected. The total number of seats flown, and the distance are added to determine RPK. RPK reimburses all miles flown by paying passengers. The total distance traveled and the number of passengers who make revenue are multiplied to determine RPK. Because it assesses the current demand for air travel, sometimes known as airline "traffic." RPK determines the amount of demand for air travel regarding the labor force or workforce by calculating the number of passengers and distance traveled [35]. Secondly, ASK includes the available seat capacity of the aircraft, and it is a decisive data for the calculation of the airline’s transporting passenger capacity. When a seat is available for carrying, it can calculate for the ASK [36]. Thirdly, PLF is the last widely accepted variable. By dividing RPK by ASK, it is determined with the airline's capability for carrying passengers. The capacity of the passenger seats has an impact on the rate at which RPK and ASK are rising. It means PLF directly affects an increase in terms of ASK. So, PLF covers supply, demand, the total passenger numbers, and seat capacity [37].

Fourthly, ATK is related to the airline’s total kilometer freight capacity. It is obtained by multiplying the distance by the total volume of capacity flown. The number of available freights is significant for the evaluation of ATK and the calculation of the airline’s transporting freight capacity. When a compartment is available for carrying, it can calculate for ATK [38]. Fifthly, RTK covers the number of kilometers flown by paid freights. It is defined as the total distance traveled with the number of freights that generate revenue. It evaluates the actual demand for air travel as an airline's "capacity." RTK calculates the amount of labor or work power used to measure the level of demand for air travel. RTK is multiplied by the distance traveled and the freight expense [39]. LF is the final extensively used variable. By dividing RTK by ATK, it is computed with the airline's capacity to move freight. RTK and ATK both rise in response to an expansion in this freight transport capacity. This indicates that CLF has a direct impact on an increase in ATK. So, CLF includes total freight capacity, total carriage volume, total supply, and total demand [40].

These factors reflect how well airlines are performing financially and operationally. IATA has shared these six variables since January 2016, so the period of the analysis starts from January 2016 [41, 42]. In this study, air passenger and freight transportation variables named RPK, ASK, PLF, ATK, RTK, and CLF analyzed in the time series modelling [43], and they obtained from the IATA Air Passenger Monthly Analysis Reports [41] and Air Freight Monthly Analysis Reports [42]. Additionally, the air passenger and freight numbers took from the Bureau of Transportation Statistics (BTS) for Air Passenger Data [44] and Air Freight Data [45].

4. Methodology

As previously determined, this research uses IATA-released monthly data from January 2016 through August 2022. These factors are listed as follows: Gross Domestic Product (GDP), Domestic Passenger Numbers, International Passenger Numbers, Domestic Freight Numbers, International Freight Numbers, Available Seat Kilometer (ASK), Revenue Passenger Kilometer (RPK), Passenger Load Load Factor (PLF), Available Cargo Tonne Kilometers (ACTK), Revenue Tonne Kilometers (RTK), and Cargo Load Factor (CLF) [35, 36]. This study includes time series modeling to forecast PLF and CLF while analyzing the contributing variables. Therefore, endogenous factors ASK, RPK, GDP, domestic, and international passenger numbers are considered in the Vector Error Correction Model (VECM), while endogenous variables CTK, ACTK, GDP, domestic, and international cargo numbers are thought to affect the CLF. After the VECM model has been applied, the relationship between PLF, CLF, and the other endogenous variables is made known to impulse response functions. In time series modeling, the series that are connected to the selected variables are transformed with a logarithmic transformation and normalized to remove variability by subtracting the mean and separating the standard deviation. To avoid NaN results caused by logarithmic transformations with negative values, plus 1 is added to all series. The time series analysis is carried out using the following packages: "TSA, vars, urca, forecast, and tsDyn" in R 4.0.2. [46]. Understanding the stationarity and connection of the series can be accomplished by looking at the standardized series (Figure 1 and Figure 2).

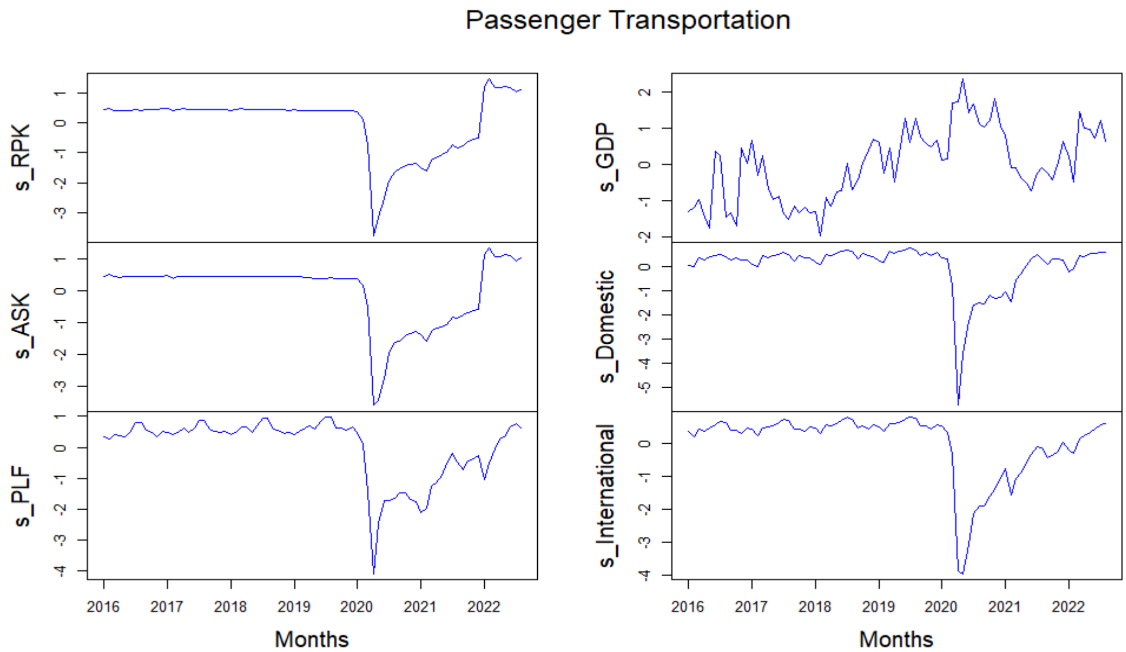


Figure 1: *The standardized time series plot of comparing s_RPK, s_GDP, s_Domestic, s_International, s_PLF and s_ASK*

In the period of January 2016 to August 2022, s_PLF, s_ASK, s_RPK, s_GDP, domestic, and international passenger number variables are shown in Figure 1. It is obvious that a major drop is reported in April 2020 due to COVID-19 impact on all series. Although the increase in every variable has slightly started and continue after May 2020. s_RPK and s_ASK variables pass their previous level at the beginning of 2022. Besides, other series approximately reach their previous level (slightly lower) at the beginning of 2022 and pass their previous level at the third quarter (July and August) of 2022.

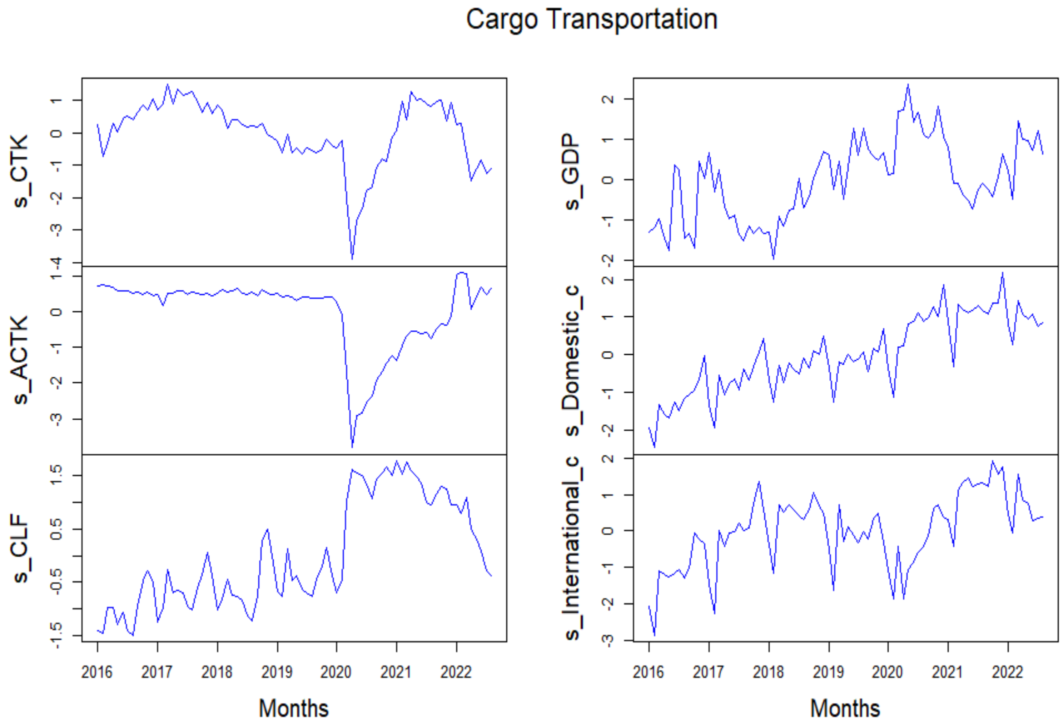


Figure 2: *The standardized time series plot of comparing s_CTK, s_ACTK, s_GDP, s_Domestic, s_International, and s_CLF*

In the period of January 2016 to August 2022, s_CTK, s_ACTK, s_GDP, s_Domestic, s_International, s_CLF parameters are shown in Figure 2. The COVID-19 Pandemic's impact is expected to result in a major drop in all data in April 2020, except for GDP. On May 1, 2020, the GDP will have increased and reached its peak value. In terms of s CLF, the series barely surpassed its prior level, but s_Domestic and s_International reached their top level in the third quarter (July to September) of 2022.

4.1. Unit root test and the lag-length determination

The idea of stationarity is very important in time series analysis. The covariance between two series values is expressed as the number of lags in the series, and a time series has a fixed mean, variance, and stationarity. Once trend and seasonality modifications have been made, time series models must be used (not changing over time). A subjective way of assessing stationarity is to use Augmented Dickey-Fuller (ADF) test statistics (47; 48]. The test is applied to a new model called the ADF test because the lags of the dependent series are expected to be added to the right of the equation to solve the autocorrelation problem. A test was suggested by Dickey et al. [49] related to issues in autoregressive time series. Here is how this test is shown.

$$\Delta y(t) = \alpha + \rho y(t-1) + \beta T + \sum_{s=1}^{p} \mathrm{d}_s \Delta y(t-s) + u_t \qquad (1)$$

In the formula, $\Delta y(t)$ is K-dimensional vector of observed variables, α is Kx1-dimensional constant vector, T is a time trend, u_t is the error term which has 0 mean and constant variance called white noise. Both the level of the series and their initial differences are tested in this procedure. In contrast to the alternative, the null hypothesis is that the series under examination has a unit root. In each example, the final prediction error (FPE) from Akaike is minimized to determine the lag-length [50]. Additionally, the Likelihood Ratio Test (LR), Akaike Information Criteria (AIC), Schwarz Information Criteria (SC), and Hannan-Quinn Information Criteria (HQ) can define the optimum lag-length. In every test except the LR test, the smallest value indicates the ideal lag-length. By putting the likelihood ratio statistics to the test at the selected level of significance, the LR test is discovered. The proper lag-length should be long enough to prevent autocorrelation between error terms but short enough to prevent any loss of information regarding the interaction of the series [51].

4.2. The cointegration test

The cointegration test determines whether there is a long-term relationship between the series after the stationary study between the series. Three alternative approaches are utilized in the literature to incorporate the cointegration test into the model. These methods were improved by Engle and Granger [52], Johansen and Juselius [53], and Pesaran, Shin, and Smith [54]. Johansen and Juselius' [53] technique was selected for this study because it allows for the examination of more than two variables. The absence of a cointegration vector in the series is the null hypothesis (H 0:r=0). A different possibility for the cointegration vector (H 0:r0) is that the time series have one (cointegrated series I(r)). R is a symbol for the quantity of cointegration vectors. If there is at least one cointegrated vector in the study, it means there is a long-term relationship between the series in the model. In other words, the order of these series remains constant. The VECM ought to be incorporated into the model because it is determined whether a long-term relationship exists at this point in the investigation.

4.3. Vector error correction model (VECM)

Long-term and short-term relationships between series are separated by VECM. Engle and Granger [46] created it to distinguish between short-term connections. It is attempted to assess whether the series experiences any shock over the long-term using VECM. According to Engle and Granger [52], the operating model for the VECM is as follows:

$$\Delta y(t) = \alpha\beta'\, y(t-1) + \Gamma_1\, \Delta y(t-1) + \cdots + \Gamma_{p-1}\, \Delta y(t-p+1) + u_t \quad (2)$$

In the formula, $\Delta y(t)$ is K-dimensional vector of observed variables, α is Kxr-dimensional coefficient matrix, β is Kxr dimensional cointegration matrix, Γ_i is kxk-dimensional short_term coefficient matrix, and u_t is the error term which has 0 mean and constant variance called white noise. The error correction variable (β) acts to maintain the model dynamics in equilibrium and compels the variables to converge on the Error Correction Term (ECT), which is the long-term equilibrium value. When the error correction term's coefficient is statistically significant, bias is present. The coefficient size is a measure of how quickly the value of the long-term equilibrium is approaching. In actual, it is anticipated that the error correction variable will be statistically significant and negative. The variables in this instance are said to move in the direction of the long-term equilibrium value. Short-term departures from equilibrium will be rectified based on the size of the error correction variable's coefficient [55]. The lag order is p. The maximum lag and minimal Akaike Information Criteria are used to choose the lag-length p in the VECM.

4.4. Impulse response functions and the decomposition of forecast error variance

The estimated coefficients in VECM are quite challenging to comprehend. Impulse-response function (IRF) graphs, which are graphical representations of the reactions to varied shocks, are thus utilized to analyze the model's results. The vertical axis is used to generate the graphs of the impulse-response functions. The amplitude and direction of other series' responses indicate an increase in the standard deviation's response to the pertinent series. In a 12-month period, the shock is given a horizontal axis. Red-dashed lines reflect confidence intervals with 2 standard errors for how the variables will respond, and they are crucial in establishing the data' statistical significance. Indicating that the reaction is statistically significant at a 95% confidence level, the bottom and higher bands both had the same sign. The dotted lines on the graphs show the confidence intervals, and the straight lines on the graphs reflect the point estimates of the effect-reaction coefficients. To verify the relationship between the series, the Forecast Error Variance Decomposition (FEVD) approach is used. A specific variable's response to its own shock and the shock from other variables are evaluated in the VECM model, or FEVD. FEVD breaks down a variable's fluctuation into its individual shocks. It simply divides the variance of each variable's forecast mistakes between its own shocks and those of the other variables in the VECM [56].

4.5. Forecasting

Recursively, forecasts are made for the series' levels. By converting VECM to a VAR in R (using the VARrep function), forecasts for VECM can be obtained. Since a VECM with a lag of p corresponds to a VAR with a lag of p + 1, the new data for a VECM with a lag of p should have p + 1 rows.

5. Results

ADF test results for evaluating stationarity, cointegration test results, estimated VECM model results (for s PLF), s PLF impulse response, forecast error variance decomposition, forecasting of s PLF, and forecast values for passenger load factor are shown in the results section with tables and figures.

5.1. Unit root test and determining delay

The unit root of the series is the null hypothesis. The time series being stationary is an alternate theory (or trend-stationary). As shown in Table 2, the number of s_ASK, s_GDP, s_Domestic, and s_ International variables all reject the null hypothesis at the 0.05 significant level. The initial difference between s_PLF and s_RPK is discovered stationary. As shown in Table 1, the null hypothesis is rejected at the 0.05 significance level.

Table 1: *ADF test results to show the evoluation of stationary*

Variables	**s_PLF**	**s_RPK (1st diff.)**	**s_ASK**	**s_GDP**	**s_Domestic**	**s_International**
ADF test value	-2.368	-6.344	-2.399	-2.497	-3.118	-2.68
p	0.039	<0.001	0.009	<0.001	0.009	0.007
Variables	**s_CLF**	**s_CTK (1st diff.)**	**s_ACTK**	**s_GDP**	**s_Domestic_c**	**s_International_c**
ADF test value	-2.331	-6.491	-2.204	-2.497	-2.798	-3.724
p	0.034	<0.001	0.018	<0.001	<0.001	<0.001

The AIC, HQ, SC, and FPE tests are considered to estimate lag-length. The structure of VECM model is used in these tests to establish the ideal lag-length for this data set, which is 10. Despite the small sample size and the series' structure, the lag-length is set at 2. So, to forecast s_ PLF and s_CLF, the cointegration test is required. It can be utilized with the series in the estimate of regressions.

5.2. The test of cointegration

r indicates the cointegration equations number. The test statistic is low for r=1 for s_PLF and r=3 for s_CLF models at 5% significance level, rejecting the hypothesis. Table 2 shows the cointegration's presence that VECM was used to find the result.

Table 2: *Cointegration test results*

s_PLF	test	10pct	5pct	1pct	s_CLF	test	10pct	5pct	1pct
r <= 5 |	2.78	6.50	8.18	11.65	r <= 5 |	1.54	6.50	8.18	11.65
r <= 4 |	6.63	12.91	14.90	19.19	r <= 4 |	5.13	15.66	17.95	23.52
r <= 3 |	12.14	18.90	21.07	25.75	r <= 3 |	**20.61**	28.71	**31.52**	37.22
r <= 2 |	19.54	24.78	27.14	32.14	r <= 2 |	50.72	45.23	48.28	55.43
r <= 1 |	**29.01**	30.84	**33.32**	38.78	r <= 1 |	83.57	66.49	70.60	78.87
r = 0 |	49.63	36.25	39.43	44.59	r = 0 |	143.89	85.18	90.39	104.20

5.3. Vector error correction model (VECM)

The acquired results led to the formation of a VECM with r=1 and r=3 cointegration vectors. As previously indicated, the model's lag length is assumed to be 2. In Table 3, the estimated VECM results are shown.

Table 3: *VECM model results with an estimation (for s_PLF)*

Response	**s_PLF**	**Response**	**s_CLF**
Variables (lags)	Estimate (Standard Error)	Variables (lags)	Estimate (Standard Error)
s_RPK(-1)	1.886 (1.510)	s_CTK(-1)	-0.021 (0.100)
s_ASK(-1)	-1.571 (1.586)	s_ACTK(-1)	-0.079 (0.130)
s_PLF(-1)	0.888 (0.280)**	s_CLF(-1)	0.231 (0.135)·
s_GDP(-1)	0.003 (0.069)	s_GDP(-1)	-0.138 (0.065)*
s_Domestic (-1)	-0.726 (0.306)*	s_Domestic_c(-1)	0.071 (0.130)
s_International(-1)	-0.168 (0.470)	s_International_c(-1)	-0.202 (0.106)·
p<0.001		p<0.001	
		ECT1=0.122 (0.042)**	
ECT1= 0.181 (1.424)		ECT2=-0.111 (0.068)	
		ECT3=-0.297 (0.105)**	

·p<0.10,*p<0.05, **p<0.001, ***p<0.0001

The Error Correction Term (ECT) controls how quickly long-run equilibrium returns. ECT1>0, ECT2>0, and ECT3>0, or at least one of them cannot be equal to 0, are necessary for a long-term connection to be stable. Table 3 shows that it does meet the prerequisite for a long-term stable connection. The error correction model will re-establish s_PLF's and s_CLF's long-term equilibrium because it is statistically significant and negative. Approximately 18% (s_PLF) and 30% (s_CLF) of the variances are corrected when there is a departure from equilibrium. The impulse-response functions are discussed in the next part to further explore the long-term impacts.

5.4. Impulse response function

For the results to be regarded as valid, both IRF confidence intervals must remain in the area above (or below) the zero band. As a result, conclusions from the research may only be drawn if the confidence intervals fall within the same range.

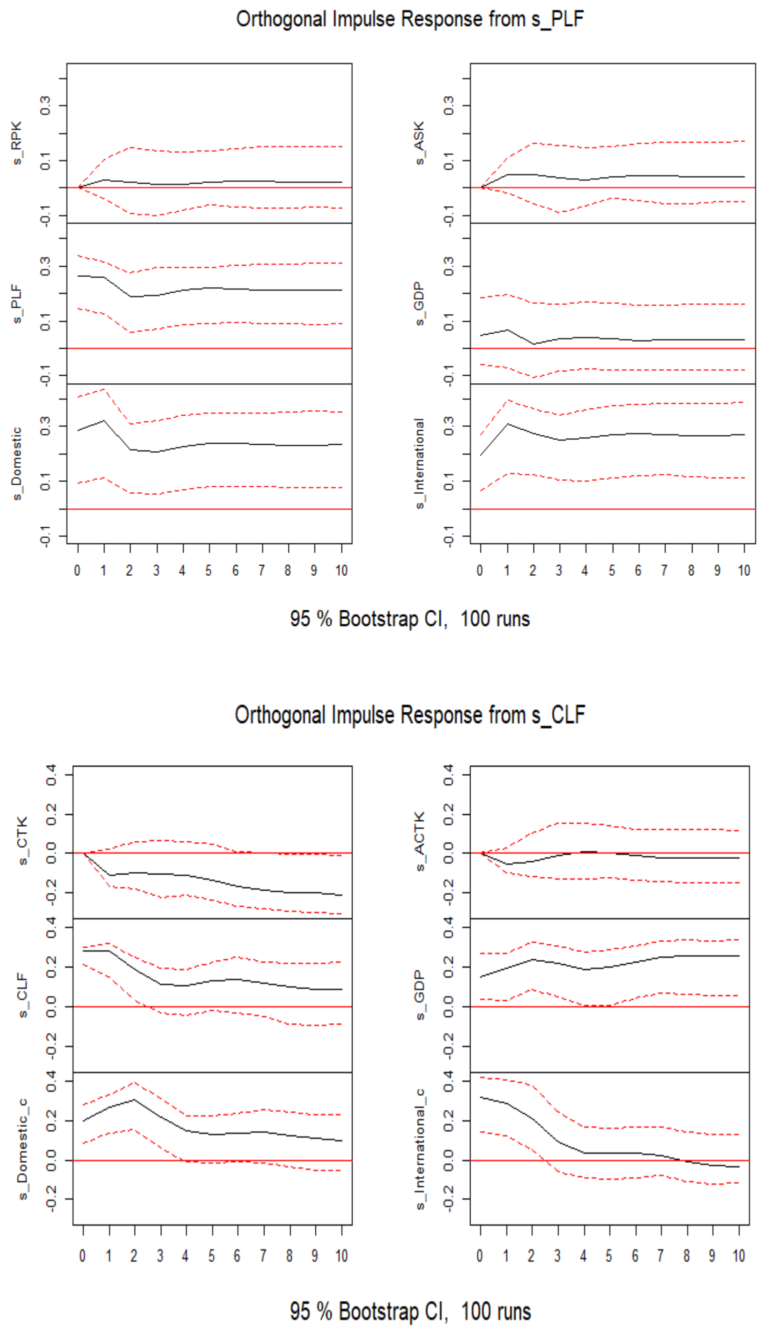
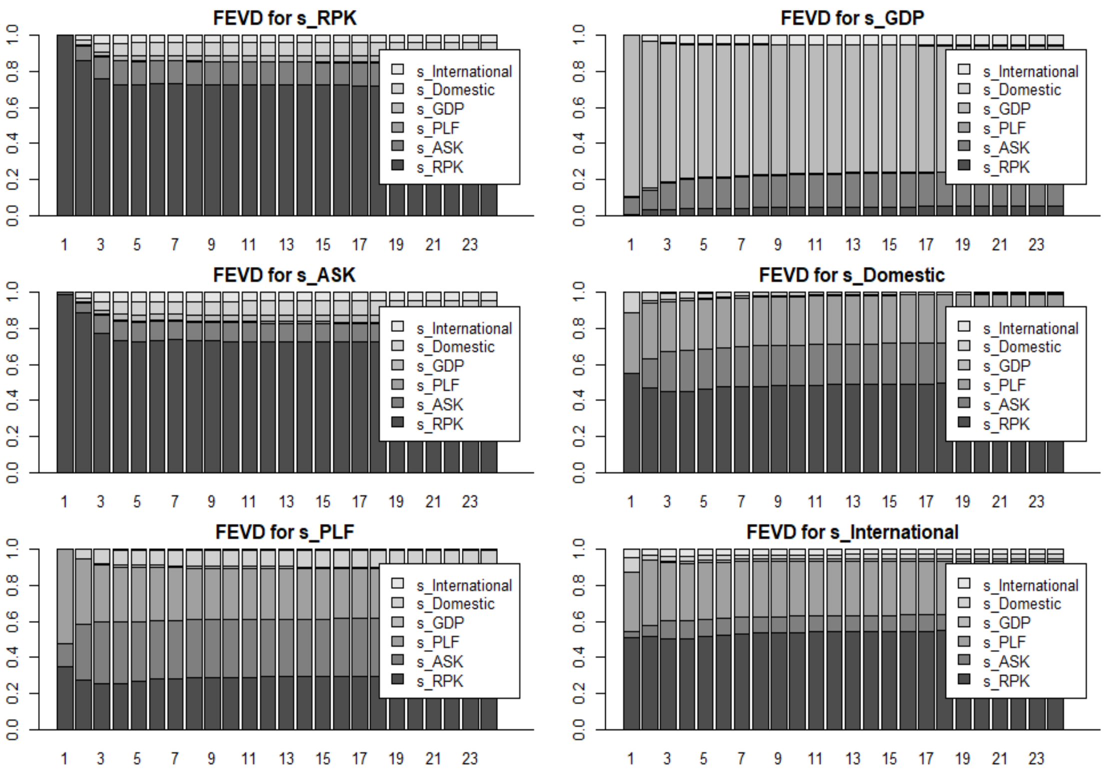


Figure 3: *s_PLF and s_CLF impulse response*

The top graph, in the middle of the left side, demonstrates that s_PLF started to fall after being temporarily touched by the effect, and then the effect disappears. According to the bottom-left graph, the short-term influence of s_Domestic_c on s_PLF increased, while the long-term effect of this impact gradually declined. The bottom right-hand graph demonstrates that after being touched by s_ International, s_PLF started to rise, and this impact gradually subsided in long-term. The bottom graph in the middle left-hand column demonstrates that s_CLF started to rise after being negatively affected by itself for a while, and eventually the effect disappears. The bottom right-hand graph demonstrates that the short-term influence of s_International_c on s_CLF was followed by an increase before the impact disappeared. The graph on the bottom left shows that s_CLF started to increase after being temporarily touched by s_Domestic_c, and subsequently this impact disappears. After being affected by s_ GDP in the near term, s_CLF started to rise, and this impact gradually lessened in long-term (Figure 3).

5.5. Decomposition of forecasting error variance

By dividing the variance of forecast error, it is possible to observe the impact of independent variables on s_PLF and s_CLF. The variance decomposition of forecast error examines the relative contributions of various variables and shocks to changes in a series. To find the impact of other series on a shock that happens in any of the series, variance decomposition is used. It defines the percentage of a shock unit that happened in one series that was brought on by changes in another.



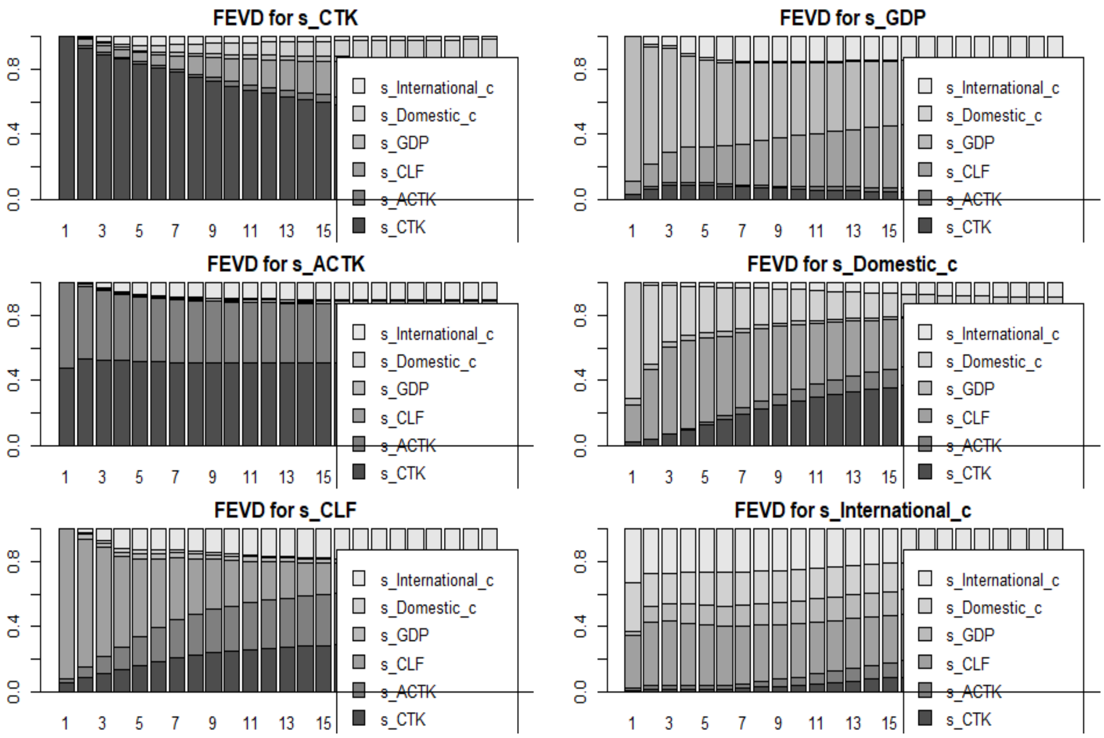
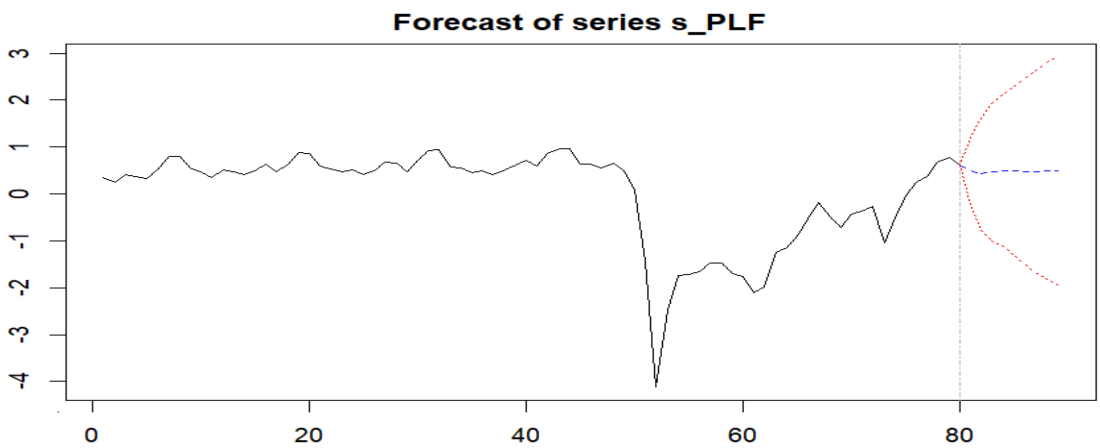


Figure 4: *Error variance decomposition of forecasting*

Figure 4 shows the FEVD results, which indicate that depending on how the series is coupled to the shock, the key variable influencing the s_PLF can alternate between the s_GDP, s_Domestic, and s_International. The primary factor influencing the s_CLF can either be s_International_c, s_GDP, or s_ CLF by itself depending on how the specific series is tied to the shock.

5.6. Forecasting

The VECM produces projected outcomes for the next nine months. Long-term results will be more accurate when the model is expanded to include the s_PLF and s_CLF values for each month. The findings of the forecast are as follows.



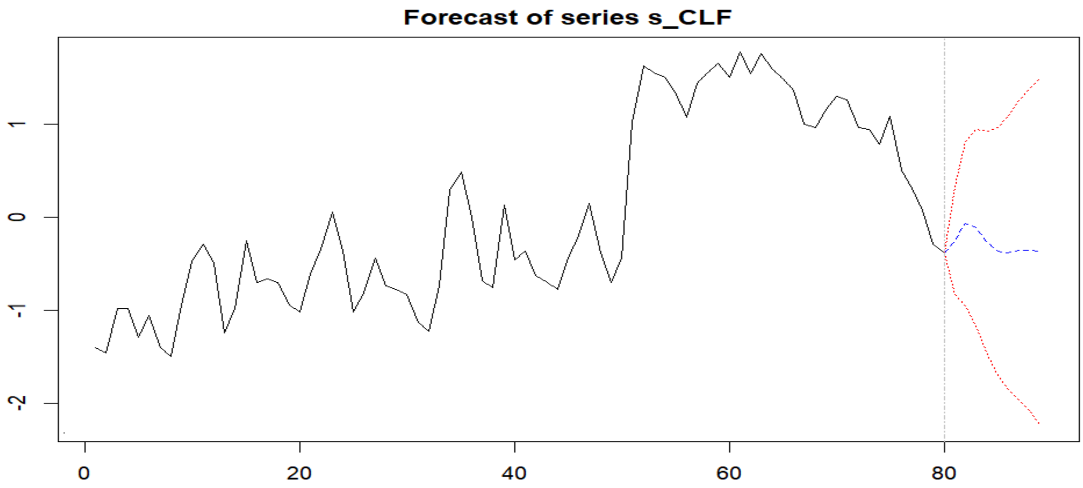


Figure 5: *The forecast of s_PLF and s_CLF*

In Figure 5, the red lines show the upper and lower boundaries, while the blue line show the conditional forecast. The s_PLF series are somewhat decreased after August whereas the s_CLF series are significantly raised after August that seen in the forecasting results in Figure 5.

Table 4: *The Forecasting Values of Passenger and Cargo Load Factor*

Date	Actual PLF	95% CI Lower Limit PLF	95% CI Upper Limit PLF	Actual CLF	95% CI Lower Limit CLF	95% CI Upper Limit CLF
August 2022	0.818	-	-	0.467	-	-
Date	**Forecast PLF**	**95% CI Lower Limit PLF**	**95% CI Upper Limit PLF**	**Forecast CLF**	**95% CI Lower Limit CLF**	**95% CI Upper Limit CLF**
September 2022	0.804	0.731	0.876	0,475	0,443	0,508
October 2022	0.797	0.676	0.919	**0,485**	0,436	0,534
November 2022	0.801	0.654	0.948	0,483	0,424	0,542
December 2022	0.804	0.640	0.969	0,474	0,407	0,540
January 2023	0.804	0.623	0.986	0,469	0,395	0,542
February 2023	0.803	0.603	1.003	0,468	0,387	0,549
March 2023	0.802	0.586	1.019	0,469	0,380	0,559
April 2023	0.803	0.571	1.035	0,470	0,373	0,566
May 2023	**0.804**	**0.558**	**1.050**	0,468	**0,365**	**0,572**

The predicted outcomes can be analyzed because model assumptions are revealed. With the VECM, the nine months forecasting can be applied to the analysis. Table 4 also includes the real data from December for comparison's sake. Due to the fall and winter seasons, it is anticipated that the slightly negative trend for s_PLF will persist for the next nine months. Therefore, the impact of the first and fourth quarters (October to December and January to March) stands a very low level. It is forecasted that the slightly upward trend will proceed in the following three months and slightly decreased in the other 6 months for s_CLF according to the potential of economic crisis in the first quarter (January to March) of 2023.

6. Conclusion

COVID-19 effect has negatively differentiated from all Pandemics and additionally crises due to its dissemination globally. Due to its nature, air transportation is the industry that mostly effected from crises and Pandemics globally. Air transportation includes air passenger and freight transportation, and they have different characteristics from each other. In general, air freight is more sophisticated than air passenger transportation because it includes more complicated processes. The calculation weight and volume, diversified services, combination, and reinforcement of network planning include more diversified specifications than passenger transportation. The significant distinctions between passenger and freight operations reveals that freight transportation have a more multidisciplinary system and higher uncertainty than passenger transportation due to the capacity problem related to volume. However, in passenger transportation passengers may cancel bookings, so the passengers that do not come to the aircraft have no place on the passenger list. Forecasting air freight capacity is also more complicated than forecasting air passenger capacity. Passenger aircraft capacity is related to total seat number in the aircraft, but freight capacity relies on the types, volume of containers and pallets named ULDs. Besides the differences between two modules of transportation, gross domestic product (GDP), total national air passenger numbers, total international air passenger numbers, total national air freight numbers, total international air freight numbers, available seat kilometer, revenue passenger kilometer, passenger load factor, available cargo tonne kilometer, revenue cargo tonne kilometer, and cargo load factor are the selected parameters for the application of time series modelling.

In the methodology part related to the analysis of air passenger transportation between January 2016 and August 2022, s_PLF, s_ASK, and s_RPK variables dramaticly decrease in April 2020 because of the COVID-19 Pandemic except s_GDP variable. Even if the increase has gradually begun and will continue to rise beyond May 2020, the series has not yet returned to its prior level (slightly lower). In the methodology part for air freight transportation between January 2016 and August 2022, s_CTK, s_ACTK, s_GDP, s_Domestic, s_International, s_CLF variables dramaticly decrease in April 2020 because of the COVID-19 Pandemic except s_GDP variable. The series returns to its former level for s_CLF, s_Domestic, and s_International with the rise trend in GDP on May 2020, although s_ GDP value has peaked. In the forecasting of a 9-month period using VECM, it is predicted that the slightly downward trend for s_PLF in air passenger transportation will continue in the coming 9 months due to weather conditions in the fourth and first quarters, whereas the slightly upward trend for s_CLF in air freight transportation will continue in the coming 3 months and slightly decrease in the remaining 6 months due to the potential economic problems globally in the first quarter. In future studies, a different analysis named Multidimensional Scaling can be applied with the same variables for all active countries in civil aviation on yearly basis.

Acknowledgments
Author has no personal interests from other parties.

Author Contributions
The author confirms contribution to the paper as follows: Data curation, Conceptualization, Investigation, Writing, Original draft preparation, Reviewing and Editing, Supervision, Resources, Methodology, Validation, Software, Formal analysis, Visualization.

References

[1] Schäfer, A. W., and Waitz, I. A. (2014). Air transportation and the environment. *Transport policy*, 34:1-4. doi: 10.1016/j.tranpol.2014.02.012

[2] Lau, H., Khosrawipour, V., Kocbach, P., Mikolajczyk, A., Schubert, J., Bania, J., and Khosrawipour, T. (2020). The positive impact of lockdown in Wuhan on containing the COVID-19 outbreak in China. *Journal of travel medicine*, 27(3). doi: 10.1093/jtm/taaa037

[3] International Air Transport Association (IATA). (2020). Airline expectations for 2020 improve ahead of virus outbreak, https://www.iata.org/en/iata-repository/publications/economic-reports/airline-expectations-for-2020-improve-ahead-of-virus-outbreak/ [retrieved 30 May 2022]

[4] International Air Transport Association (IATA). (2020). Economic Performance of the Airline Industry. iata.org/en/iata-repository/publications/economic-reports/airline-industry-economic-performance---december-2019---report/ [retrieved 30 May 2022]

[5] Air Freight. (2022). Retrieved From https://www.saloodo.com/logistics-dictionary/air-freight/ [retrieved 28 August 2022]

[6] Alekseev, K. P. G., and Seixas, J. M. (2009). A multivariate neural forecasting modeling for air transport-preprocessed by decomposition". *Journal of Air Transport Management*, 15(5):212-216.

[7] Xie, G., Wang, S., and Lai, K. K. (2014). Short-term forecasting of air passenger by using hybrid seasonal decomposition and least squares support vector regression approaches. *Journal of Air Transport Management*, 37:20-26. doi: 10.1016/j.jairtraman.2014.01.009

[8] Han, D. L., Tang, L. C., and Huang, H. C., (2010). A Markov model for single-leg air cargo revenue management under a bid-price policy. *European Journal of Operational Research*, 200(3): 800-811. doi: 10.1016/j.ejor.2009.02.001

[9] Nobert, Y., and Roy, J. (1998). Freight handling personnel scheduling at air cargo terminals. *Transportation Science*, 32(3):295-301.

[10] Boeing Company. (2016). World air cargo forecast 2014–2015.
http://www.boeing.com/assets/pdf/ commercial/cargo/wacf.pdf [retrieved 31 August 2021]

[11] Li, Y., Tao, Y., and Wang, F. A. (2009). Compromised large-scale neighborhood search heuristic for capacitated air cargo loading planning. *European Journal of Operational Research*, 199(2):553-560. doi:10.1016/j.ejor.2008.11.033

[12] Ou, J., Hsu, V. N., and Li, C. L. (2010). Scheduling truck arrivals at an air cargo terminal. *Production and Operations Management*, 19(1):83-97. doi: 10.3401/poms.1080.01068

[13] Ferguson, J., Kara, A. Q., Hoffman, K., and Sherry, L. (2013). Estimating domestic US airline cost of delay based on European model. *Transportation Research Part C: Emerging Technologies*, 33:311-323. doi: 10.1016/j.trc.2011.10.003

[14] Feng, B., Li, Y., and Shen, Z. J. M. (2015). Air cargo operations: Literature review and comparison with practices. *Transportation Research Part C: Emerging Technologies*, 56:263-280.
doi: 10.1016/j.trc.2015.03.028

[15] International Air Transport Association (IATA). (2020). COVID-19. Third Impact Assessment, 24 March 2020. https://www.iata.org/en/iata-repository/publications/economic-reports/third-impact-assessment/ [retrieved 25 August 2022]

[16] Gudmundsson, S. V., Cattaneo, M., and Redondi, R. (2021). Forecasting temporal world recovery in air transport markets in the presence of large economic shocks: The case of COVID-19. *Journal of Air Transport Management*, 91:102007. doi: 10.1016/j.jairtraman.2020.102007

[17] Truong, D. (2021). Estimating the impact of COVID-19 on air travel in the medium and long term using neural network and Monte Carlo simulation. *Journal of Air Transport Management*, 96:102126. doi: 10.1016/j. jairtraman.2021.102126

[18] Wang, S., and Gao, Y. A. (2021). Literature review and citation analyses of air travel demand studies published between 2010 and 2020. *Journal of Air Transport Management*, 97:102135.

doi: 10.1016/j. jairtraman.2021.102135

[19] Dube, K., Nhamo, G., and Chikodzi, D. (2021). COVID-19 pandemic and prospects for recovery of the global aviation industry. *Journal of Air Transport Management,* 92:102022. doi: 10.1016/j.jairtraman.2021.102022

[20] Li, X., Groot, M. de, and Bäck, T. (2021). Using forecasting to evaluate the impact of COVID-19 on passenger air transport demand, *Decision Sciences.* doi: 10.1111/deci.12549

[21] Zhang, H., Song, H., Wen, L., and Liu, C. (2021). Forecasting tourism recovery amid COVID-19. *Annals of Tourism Research,* 87:103149. https://doi.org/10.1016/j.annals.2021.103149

[22] Xuan, X., Khan, K., Su, C. W., and Khurshid, A. (2021). Will COVID-19 Threaten the Survival of the Airline Industry?. *Sustainability,* 13(21):11666. doi: 10.3390/su132111666

[23] Khan, S. A. R., Qianli, D., SongBo, W., Zaman, K., and Zhang, Y. (2017). Travel and tourism competitiveness index: The impact of air transportation, railways transportation, travel and transport services on international inbound and outbound tourism. *Journal of Air Transport Management,* 58:125-134. doi: 10.1016/j.jairtraman.2016.10.006

[24] World Travel and Tourism Council (WTTC). (2018). Travel & tourism: Economic Impact 2017. [retrieved 30 July 2021]

[25] International Air Transport Association (IATA). (2020). May Passenger Demand Shows Slight Improvement. https://www.iata.org/en/pressroom/pr/2020-07-01-02/ [retrieved 10 August 2021]

[26] Transport&Environment (T&E). (2021) Greenpeace, Carbon Market Watch Airline Bailout Tracker. https://www.transportenvironment.org/sites/te/files/Airline-bailout-tracker [retrieved 10 August 2022]

[27] Browne, A., St-Onge Ahmad, S., Beck, C. R., and Nguyen-Van-Tam, J. S. (2016). The roles of transportation and transportation hubs in the propagation of influenza and coronaviruses: a systematic review. *Journal of travel medicine,* 23(1), tav002.

[28] Bartodziej, P., Derigs, U., Malcherek, D., and Vogel, U. (2009). Models and algorithms for solving combined vehicle and crew scheduling problems with rest constraints: an application to road feeder service planning in air cargo transportation. *OR spectrum,* 31(2):405-429. doi: 10.1007/s00291-007-0110-7

[29] Leung, L. C., Van Hui, Y., Wang, Y., and Chen, G. A. (2009). 0–1 LP model for the integration and consolidation of air cargo shipments. *Operations Research,* 57(2), 402-412.

[30] Wang, Y. J., and Kao, C. S. (2008). An application of a fuzzy knowledge system for air cargo overbooking under uncertain capacity. *Computers & Mathematics with Applications,* 56(10):2666- 2675. doi: 10.1016/j.camwa.2008.02.049

[31] Amaruchkul, K., Cooper, W. L., and Gupta, D. (2011). A note on air-cargo capacity contracts. *Production and Operations Management,* 20(1):152, 162. doi: 10.1111/J.1937-5956.2010.01158.x

[32] Petersen, J. (2007). Air freight industry-white paper. Georgia Institute of Technology.

[33] Convention on the Organisation for Economic Co-operation and Development (OECD) Data. (2022). Gross Domestic Product (GDP). https://data.oecd.org/gdp/gross-domestic-product-gdp.htm [retrieved 31 October 2022]

[34] Federal Reserve Bank of St. Louis. (2022). https://fred.stlouisfed.org/series/GEPUCURRENT [retrieved 31 October 2022]

[35] Revenue Passenger Kilometers. (2022). https://airlinegeeks.com/2016/01/17/airline-metrics-revenue-passenger-kilometers/ [retrieved 31 October 2022]

[36] Available Seat Kilometers. (2022). https://airlinegeeks.com/2015/12/28/airline-metrics-available-seat-kilometers/ [retrieved 31 October 2022]

[37] Passenger Load Factor. (2022). https://airlinegeeks.com/2016/01/29/airline-metrics-passenger-load-factor/ [retrieved 31 October 2022]

[38] Available Tonne Kilometers. (2022). https://airlinegeeks.com/2015/12/28/airline-metrics-

available-tonne-kilometers/ [retrieved 31 October 2022]

[39] Revenue Tonne Kilometers. (2022). https://airlinegeeks.com/2016/01/17/airline-metrics-revenue-tonne-kilometers/ [retrieved 31 October 2022]

[40] Cargo Load Factor. (2022). https://airlinegeeks.com/2016/01/29/airline-metrics-passenger-load-factor/ [retrieved 31 October 2022]

[41] International Air Transport Association (IATA). (2022). Air Passenger Monthly Analysis Reports.https://www.iata.org/en/publications/economics/?Search=&EconomicsL2=146&Ordering=DateDesc [retrieved 01 November 2022]

[42] International Air Transport Association (IATA). (2022). Air Freight Monthly Analysis Reports.https://www.iata.org/en/publications/economics/?Search=&EconomicsL2=147&Ordering=DateDesc [retrieved 01 November 2022]

[43] Tsai, W. H., and Kuo, L. (2004). Operating costs and capacity in the airline industry. *Journal of air transport management,* 10(4):269-275.
doi: 10.1016/j.jairtraman.2004.03.004

[44] Bureau of Transportation Statistics (BTS). (2022). Air Passenger Data.
https://www.transtats.bts.gov/Data_Elements.aspx?Data=1 [retrieved 01 November 2022]

[45] Bureau of Transportation Statistics (BTS). (2022). Air Freight Data.
https://www.transtats.bts.gov/freight.asp [retrieved 01 November 2022]

[46] Pfaff, B. (2008). VAR, SVAR and SVEC models: Implementation within R package vars. *Journal of statistical software,* 27:1-32.

[47] Dickey, D. A., and Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association,* 74(366a):427-431.
doi: 10.1080/01621459.1979.10482531

[48] Dickey, D. A., and Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica: journal of the Econometric Society,* 1057-1072.

[49] Dickey, D. A., Hasza, D. P., and Fuller, W. A. (1984). Testing for unit roots in seasonal time series. *Journal of the American statistical Association,* 79(386):355-367.

[50] Akaike, H. (1969). Fitting autoregressive models for prediction, *Annals of the institute of Statistical Mathematics,* 21(1):243, 247.

[51] Kasapoğlu, Ö., and Müdürlüğü, P. G. (2007). *Parasal aktarim mekanizmalari: Türkiye için uygulama.* TCMB Uzmanlık Yeterlilik Tezi, Ankara: Şubat. 2007.

[52] Engle, R. F., and Granger, C. W. (1987). *Co-integration and error correction: representation, estimation, and testing.* Econometrica: journal of the Econometric Society, 251, 276.

[53] Johansen, S., and Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration—with appucations to the demand for money. *Oxford Bulletin of Economics and statistics,* 52(2):169, 210.

[54] Pesaran, M. H., Shin, Y., and Smith, R. J., (2001). Bounds testing approaches to the analysis of level relationships. Journal of applied econometrics, 16(3):289-326. doi: 10.1002/jae.616

[55] Enders, W. (1995). *Applied Econometric Time Series, John Wiley&Sons. Inc.,* New York, 365, 366.

[56] Omisakin, D., and Olusegun, A. (2008). Oil price shocks and the Nigerian economy: a forecast error variance decomposition analysis. *Journal of Economic Theory,* 2(4):124, 130.