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Forecasting Recovery Period of the Airfreight Transportation from Covid-19 Pandemic by using Time Series Modelling

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ABSTRACT

COVID-19 has a dramatically negative effect globally, so all transportation modes also airfreight have been affected negatively. This study aims to forecast the airfreight load factor by applying time series to the selected variables. After providing general information about COVID-19, the forecasting results apply to the time series modeling finding the getting back time into the recovery period. It analyzes between January 2016-May 2021 with available tonne-kilometer, revenue tonne-kilometer, load factor, gross domestic product, domestic and international freight. The findings show that the cargo load factor is affected by domestic transportation in the long-term and international transport in the short-term periods. So, airfreight is firstly affected by international transport due to its global position. The forecast results show that the recovery period started in February 2021 and will continue with a robust growth trend in July 2021 due to the changing airlines' focus on freight transportation. After the completion of vaccination, primarily related to passenger transportation, airfreight transportation also benefits from this growth trend with the configuration change of aircraft'. This paper's contribution shows the necessity to minimize the economic damage by using passenger aircraft for freight transport to increase the speed of the recovery period in terms of GDP.

KEYWORDS: COVID-19 · forecasting · vector error correction model · airfreight transportation · load factor.

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INTRODUCTION

Airfreight defines as the shipment of goods by an air carrier. Air transport services are significant when these goods are carried globally. Passenger airlines also carry freight in the same compartment near baggage. Airfreight is also related to all processes for freight transportation by air. When these goods carry between different places, all processes for the movement of goods define as freight. Besides, the total paid charges for airfreight show the unit price according to the type of freight [1]. Airfreight transportation has gained importance with the COVID-19 Pandemic according to the total airfreight numbers from IATA Airfreight Monthly Analysis Reports [2]. This paper examines the variables available tonne-kilometer, revenue tonne-kilometer, load factor, gross domestic product, and domestic, and international cargoes. It is for finding the forecasting results that show the recovery period. The International Air Transport Association (IATA) published a report in January 2020 before the spread of COVID-19 [3]. This report anticipated an increment of revenue passenger kilometers (RPKs) development of 4.1% and a freight tonne-kilometers (FTKs) growth of 2.0% in 2020 in the civil aviation industry. After this report, IATA analyzed the statistics for the industry a lot of times because it became clear that COVID-19 would negatively affect the development of the civil aviation industry. Since the year 2000, the annual growth of air freight transportation has been more than 7% [4]. After COVID-19 started, the airlines specialized in freight transportation. This specialization includes three strategies. The first strategy is to carry more freights in passenger aircraft near baggage. The second strategy is to change aircraft configuration by removing passenger seats to benefit freight transportation. The third strategy is buying and renting more cargo aircraft [5]. Tables 1, and 2 show the top 10 countries and companies in total airfreight carriage at the end of 2020. Table 3 shows the top airfreight companies in total carriage and revenues at the end of 2021.

Table 1: The ranking of countries in airfreight

Rank	Country	Total Freight Most Recent Value (Million Ton-KM)
1	United States	42985
2	China	25256
3	Republic of Korea	11930
4	Japan	9421
5	Germany	7970
6	Russian Federation	6811
7	United Kingdom	6198
8	Turkey	5949
9	France	4444
10	Canada	3434

Source: [6].

Table 2: Top airfreight companies in total carriage

Ranking	Company	Headquarters	Airfreight (Million Tons)
1	DHL Supply Chain & Global Forwarding	Germany	2051
2	Kuehne + Nagel	Switzerland	1643
3	DB Schenker	Germany	1162
4	DSV Panalpina	Denmark	1071
5	UPS Supply Chain Solutions	United States	966
6	Expeditors International of Washington	United States	955
7	Nippon Express	Japan	753
8	Bollore Logistics	France	634
9	Kintetsu World Express	Japan	601
10	Hellmann Worldwide Logistics	Germany	587

Source: [7].

Table 3: Top airfreight companies in total revenues

Ranking	Company	Headquarters	Airfreight (Million $)
1	UPS Supply Chain Solutions	United States	30056
2	FedEx Corporation	United States	23539
3	Uber	United States	20478
4	JR	Japan	11697
5	DHL Supply Chain & Global Forwarding	Germany	9513
6	BNSF	United States	7635
7	Union Pacific	United States	7536
8	SF Express	China	7035
9	China Post	China	6001
10	McLane	United States	5867

Source: [8].

Before COVID-19, the airfreight sector was popular but did not have enough global importance. COVID-19 Effect has increased this global popularity. For instance, at the end of 2017, the total revenue in airfreight of the big ten integrators was approximately 100000 Million $. At the end of 2021, this revenue reached approximately 130000 Million $. In addition to these numbers, the airfreight distribution can classify as; integrators with full cargo airlines %52, combinational %36, and passenger airlines %12 [9]. When it is examined the airlines except for integrators, the total freight revenue of all airlines was 114410 Million $ in 2018, 103460 Million $ in 2019, 110800 Million $ in 2020, and reached 122960 Million $ in 2021. The world's most valuable ten companies' total freight revenue in 2021 was 129357 Million $. These numbers show that the top ten valuable integrators cover more than %80 percent of all integrators, and their value is more than all airlines that use the combinational and passenger transport strategy [10].

The main contribution of this paper is to express the increasing trend of airfreight transportation during the pandemic by giving recommendations to the airlines in freight transportation mentioned before with three strategies. Besides the main contribution, when the Pandemic's second year finished in January 2022, it seems that the recovery trend of passenger transportation exceeded %75 percent before the Pandemic, and the airfreight transportation exceeded %110 percent (%10 percent more before the Pandemic). These numbers show the importance of airfreight transport for the airlines during the Pandemic is more than air passenger transportation. Therefore, the European Organisation for the Safety of Air Navigation, commonly known as Eurocontrol [11], shows daily data of all European Airlines. These data have revealed that air passenger transportation has a positive trend by getting support from the Summer Season [11]. Furthermore, the data taken from the IATA Airfreight Monthly Analysis Reports specified that the airfreight numbers have a positive increasing trend more than air passenger transportation [2]. This paper shows the faster recovery trend of airfreight rather than passenger transportation and the positive effect of airfreight on the GDP level of countries. The study's purpose is to analyze the last five years and the five months (access of the data between January 2016 and May 2021) of air freight transportation. The forecast applied for the recovery time until November 2021. Additionally, the term recovery time means that the emergence of similar figures is in line with the reached total traffic data pre-COVID-19. This study is essentially related to finding COVID-19 impact on airfreight transportation and the recovery (or growing) period of COVID-19 using time series modeling. It also evaluates the GDP with national, and international transportation of airfreight all over the world. The context of this study includes the literature review in section 2, a sample of data with the selected variables using time series analysis in section 3, the methodology with the analysis of the time series modeling in section 4, the results with the findings of the analysis in section 5, and the discussions/conclusions part with summarizing the study in section 6.

LITERATURE REVIEW

In this section, it was defined the related studies about transportation. However, the papers about the recovery of air transportation wrote at the beginning period of COVID-19. Hence the difference in this study shows the recovery period clearly because the previous papers mentioned the negative trend of COVID-19, and they are far away from the recovery trend. This study includes the data from the year 2021, thus it mentioned the positive trend of airfreight transportation in COVID-19. 17 research found about the recovery trends, COVID-19, similar models.

Firstly, Gudmundson et al. [12] published a study about forecasting the relation between the strength of economic shocks and the temporal recovery of the worldwide air transport industry. In this study, based on the worldwide especially passenger flight demand, it is estimated that it will take at least 2.4 years (recovery by end-2022) for flight volume to return to pre-COVID-19 levels. The most hopeful prediction for the recovery specify as two years (recovery by third-quarter-2022), and the most depressing estimation specify as six years (recovery in 2026). In this study, the ARIMAX methodology is used to forecast the recovery in a univariate manner for each passenger and freight [12]. They published this study at the beginning of the year 2021. So, this study is far away from the recovery mentioned before. Truong [13] published a study related to air transportation. It is related to analyzing the number of domestic and international flights. This study revealed that flight numbers in the pandemic may not be at 2019 levels, however, these numbers have not so far from the demand for transportation in 2019. The purpose of that paper was to develop and test neural network models for estimating domestic and international air transportation in the medium and long term. This estimation determined passenger demand by examining the economic conditions after COVID-19 that posed prohibitions on transportation. Wang and Gao [14] examined 87 papers about air transportation. They examined the papers between 2010 and 2020. They analyzed the input data with preliminary analytic methods. The input data was designed and conducted for three analyses. These analyses found the connection between these reviewed researches. This research examined air travel demand at the national level by applying time series for the socio-economic and airline operational factors to forecasting.

Dube et al. [15] specified when air travel is active, the problems cannot recover immediately. For instance, protecting passengers, reducing ticket prices, increasing efficiency, guaranteeing quality in-flight services, and sustaining to protect the health and safety of passengers are also necessary. Li et al. [16] specified that the COVID-19 caused a dramatic decline in passenger air transportation because of two factors. These are; supply prohibition and demand breakdown. The study divided passengers by their characteristics, simulating diversified scenarios, and forecasting demand for each segment. Zhang et al. [17] specified that econometric and judgmental strategies estimated the probable trends of tourism recovery in Hong Kong. These forecasts interpreted the economic influences of the COVID-19 Pandemic on tourism in Hong Kong. Xuan et al. [18] examined the COVID-19 effect on airline incomes by examining the recovery period in general. They estimated the recovery period by using the vector autoregression method. The findings show that gross domestic product (GDP) and airfreight transportation are the best determinants. Zhao et al. [19] specified that the findings demonstrated that global dry bulk transportation was generally influenced by lockdown strategies still in February 2022 during COVID-19, and the Baltic Dry Index offered a year-on-year reduction of about 35.5% from 2019 to 2020. Barua et al. [20] determined the analysis of learning improvement model applications in diversified perspectives of International Freight Transportation Management. Alexander and Merkert [21] aim to interpret whether gravity models are vigorous to estimate the considerable economic shocks like the Global Financial Crisis (GFC). Shardeo [22] analyzed the container traffic at three Indian major ports between 1999 and 2019. Two models were used to forecast. Grey Forecasting and AutoRegressive Integrated Moving Average (ARIMA) models analyzed the container traffic data. Schramm and Munim [23] forecasted freight rates in container shipping by combining inquiries between practitioners about their reliance, or sensation for the developments in current and future market options. Shardeo et al. [24] determined diversified factors about Blockchain Technology adoption in freight transportation. It implemented an integrated Fuzzy Analytic Network Process (FANP) to reveal the success factors.

Grosche and Heinzl [25] recommended two gravity models for forecasting air passenger numbers between city pairs. These models include the variables about general economic activity and geographical characteristics of city pairs for the determinants that defined air service properties. Boonekamp et al. [26] recommended an extensive gravity model for the most significant variables in air travel demand that determined to use of a two-stage least squares technique. Hsiao and Hansen [27] improved an air passenger model related to the generation of city-pair demand and demand assignment in a single structure. Birolini et al. [28] recommended an origin-based demand model for air travel which supposed saturation at the origin level and clearly explained substitutability among destinations. Chowdhury et al. [29] categorized the influences of COVID-19 to show how the issue of supply chain affected demand, productivity, use of sources, transport, logistics, relationships, the performance level, and sustainability. The purpose of this research assures to clear up the influences of COVID-19 on the supply chain. Deng et al. [30] measured the trend of the Chinese Scheduled Freighter Network (CSFN) via topological characteristics and have detected how this system altered after COVID-19. With the usage of spatial analysis with the Complex Network Theory (CNT), CSFN demonstrated network properties in the midst of COVID-19. Cattaneo et al. [31] improved a connected modeling structure that ensures a decision support appliance for airlines' frequency planning in the status related to a multi-airport system.

Besides these studies, Baidya et al. [32] specified that air transportation has a lot of real-life problems that can be corrected with strategic solutions. COVID-19

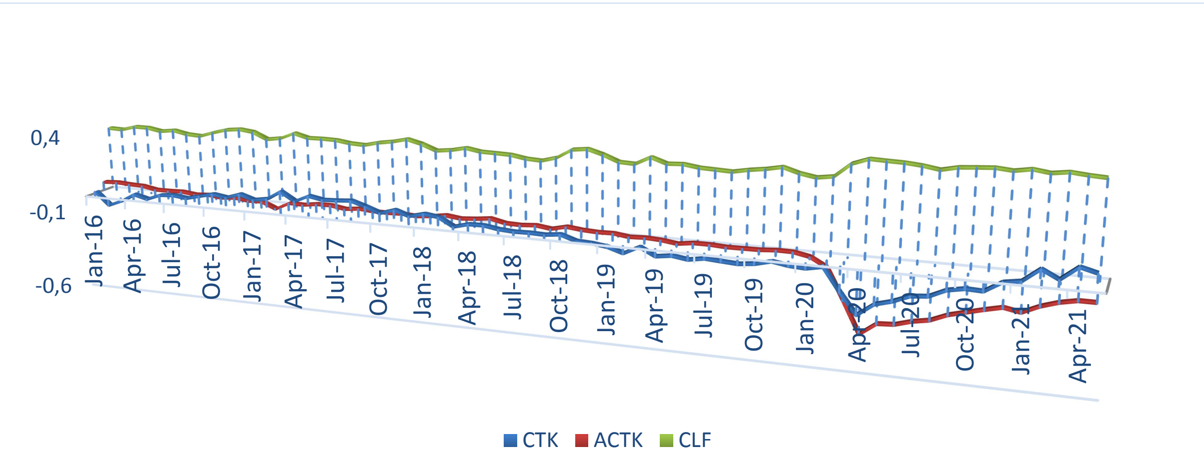

Figure 1: IATA air cargo market analysis
Source: IATA Air Freight Monthly Analysis Reports [2].

is the most significant real-life problem that affected nearly all countries negatively. However, this negative effect triggered airfreight transportation positively, and in one year the total freight numbers reached the numbers before COVID-19. Because the airlines and also airfreight companies adapted their strategies to real-life problems like Baidya et al. [32] determined before. However, different waves of COVID-19 did not correctly and deeply analyzed in the first year of COVID-19. Furthermore, the specialization in the vaccination process has changed globally. After one year passed, IATA's declining air cargo trend changed positively in February 2021. Figure 1 shows these numbers related to air cargo transportation have been on a rising trend since February 2021.

The airfreight concept describes with two general expressions. Firstly, airfreight is a complicated system including socio-technical specifications and has a broad number of different specifications [33]. For instance, the fast progress of economic globalization and raised air traffic demand comprises a decision-making process for the development of airfreight [34]. The concept of an integrator is significant in this development, and it defines as using at least two transportation modules when shipping the products to the customer. Tables 2, and 3 show that the most successful integrators in airfreight networks like DHL, and UPS apply these processes under the total metric tonne and financial conditions with a well-designed structure in air transportation for the worldwide framework of civil aviation [35]. In addition, in the first three tables, the ranking of countries in airfreight, the ranking of companies in airfreight (metric tons), and top airfreight companies according to their total revenue cover more than %30 percent of total airfreight globally (the total integrator percentage is %43). Secondly, airfreight describes as the transport of any commodity such as cargo, mail, or express parcels transported by air. These freights can be carried by integrators (DHL, UPS), full cargo airlines (having only cargo aircraft, for example, Cargolux), combinational airlines (having passenger and cargo aircraft, for example, Turkish Airlines), and passenger airlines (carrying freights near baggage in the same compartment, for example, Pegasus Airlines). If the aircraft is wide-body, the loading area fills with unit load devices (ULD: used with a container for baggage and pallet for freights). If the passenger aircraft is narrow-body, the loading area fills with baggage and freights in the belly area. So, it seems that there have crucially decisive advantages of airfreight transportation more than other freight transport modules such as the marine (sea), road, and rail [36].

This study aims to find the airfreight development rate by analyzing the selected variables before and after COVID-19. It also analyzed how this rate is primarily affected by the GDP. Accordingly, air cargo development has essentially outperformed in periods of increase in trade. When the high-level cyclical civil aviation industry scale down, air freight can recover its position faster than air passenger transportation. In the downturn period caused by Pandemics and economic crises, the dynamics of airfreight is a progressively significant indicator related to the large countries' economies that will be going. So, the considerable position of airfreight enlarges the chain of trade and supply in a competitive environment. Airfreight transportation is a significant part of worldwide trade and supply chains, associated heavily with economic development. When the suppliers, manufacturers, and markets developed at the worldwide level, the significance of freight transportation was well developed. On the other side of the issue, although the major expenses related to the efficiency of high-cost operations, airfreight transportation has continued its development trend. Hence, this development trend has also reverberated on the GDP of the countries [37]. In the light of such information, air freight evaluates as a commodity, revenue, and labor for countries. The management of these issues composes extensive processes in the development area. It is also related to the GDP level of the countries [38].

After examining the flag carrier and full-service airlines' fleet, it seems that during the Pandemic between May 2020 - May 2021 approximately %20 of all aircraft were used for freight transportation. This number is %5 more than before the Pandemic. This ratio shows a %33 increase in aircraft usage for freight transportation [39]. Furthermore, IATA specified the use of "passenger-freighters" as being "costly and complex to operate." The use of passenger aircraft for freight transportation is considered the best of the bad. Despite the costly and complex operation problem related to the staying of aircraft on the ground, the majority of the aircraft includes the fleet with the strategy of financial leasing that cannot be used during the Pandemic. Indeed, it is more advantageous to use the cargo aircraft with its main purpose. In this point of view, such a strategy applies due to the low number of aircraft in this configuration that is inside the fleet. Because of the financial crisis, it is risky to lease and buy aircraft during the Pandemic [40]. To sum up, the literature review covers the general knowledge of airfreight transportation and the negative effect of COVID-19 on the airfreight numbers at the first peak of the Pandemic with the globally increasing trend of airfreight after the first peak of this Pandemic finished.

SAMPLE OF DATA

There have three basic airline variables for airfreight transportation. They use to analyze the operational and financial performance of airlines. These variables are selected and taken from the IATA Airfreight Monthly Analysis Reports [2]. These are; available tonne-kilometers (ATK or ACTK: available cargo tonne-kilometers), revenue tonne-kilometers (RTK or CTK:

cargo tonne-kilometers), and load factor (LF or CLF: cargo load factor). These three parameters are taken for the time series to examine the whole monthly periods of 2016, 2017, 2018, 2019, 2020, and the first five months of 2021. In addition, since a minimum of 50 months of data is needed for the predictions made with time series models to be valid and reliable, the study did not distinguish between before and after the pandemic [41]. So, the selected parameters named;

First of all, ACTK includes total freight capacity and total kilometers. ACTK acquires by multiplying the total kilometers and the number of the flown total volume of freight capacity. The available compartment number is significant for the evaluation of ACTK, and also to calculate a freight transporting capacity. So, the volume and number of a kilometer are significant data for ACTK, hence it is selected as a variable [42]. Secondly, CTK is related to the flown number of kilometers by carried cargo. It calculates as the revenue-generating freight numbers multiplied by the total distances. Since it evaluates the actual demand for air transportation, it defines occupancy rate and capacity. So, the total carriage and number of a kilometer are significant data for CTK, thus it is selected as a variable [43]. The last widely used airline industry variable is CLF. It calculates the airline's freight transporting capacity by dividing CTK by ACTK. If the freight capacity is suitable for the CLF numbers that are not in a decreasing trend, CTK and ACTK also increase. It means that CTK is directly related to an increment in ACTK with the undeceased trend of CLF numbers so as not to confuse demand and supply concepts. Besides, CLF is selected as a variable also for forecasting, and it is related to the volume, the number of a kilometer, and total carriage of airfreight [44].

In the analysis, ACTK and CTK variables examine with year-on-year % change by comparing the same period of the previous year. However, the CLF variable examines the actual value of the same year's performance. All of these three variables take starting from January 2016. IATA shared all these three variables with three types starting from this period. In this study, the data was taken from the IATA website as airfreight transportation, so ACTK, CTK, and CLF variables use to forecast the time series model [45]. Because these variables are the only ones to evaluate the trend of airfreight. They select the time series modeling ATK, RTK, and LF. They took from the IATA Airfreight Monthly Analysis Reports [2]. The theoretical foundation of ACTK and CTK includes the potential that they affected CLF in the time series forecasting model. ACTK shows the available freight capacity of a freight-use aircraft, CTK shows the total carrying freight of freight-use aircraft, and CLF shows the capacity used efficiently. So, CLF has a connection with ACTK and CTK to predict the forecasting model. Additionally, the monthly data for airfreight transportation took from the Bureau of Transportation Statistics [36]. In this study, monthly numbers of domestic freight, international freight, and GDP took for the time series. The parameter which affected the air transportation numbers selects as GDP. GDP is the whole financial or market value of the whole raw materials. They include goods and services inside the border of countries in a particular period. As a spacious assessment of all national production, it works as a detailed scorecard of a founded country's economic welfare. GDP is usually measured yearly, however, it is also occasionally calculated monthly as taken in this study therewithal [46]. Furthermore, all GDP variables took from the Federal Reserve Bank of St. Louis [47]. GDP specifies as the financial, and the other variables specify as the operational variables. GDP variable is a sole determinant to find the financial status of countries because it has a direct connection with other variables that are specified as operational.

MATERIALS AND METHODS

This paper aims to forecast the recovery period of COVID-19 by the potential variables that may affect airfreight numbers described at the beginning of the sample of the data section. Furthermore, to forecast the

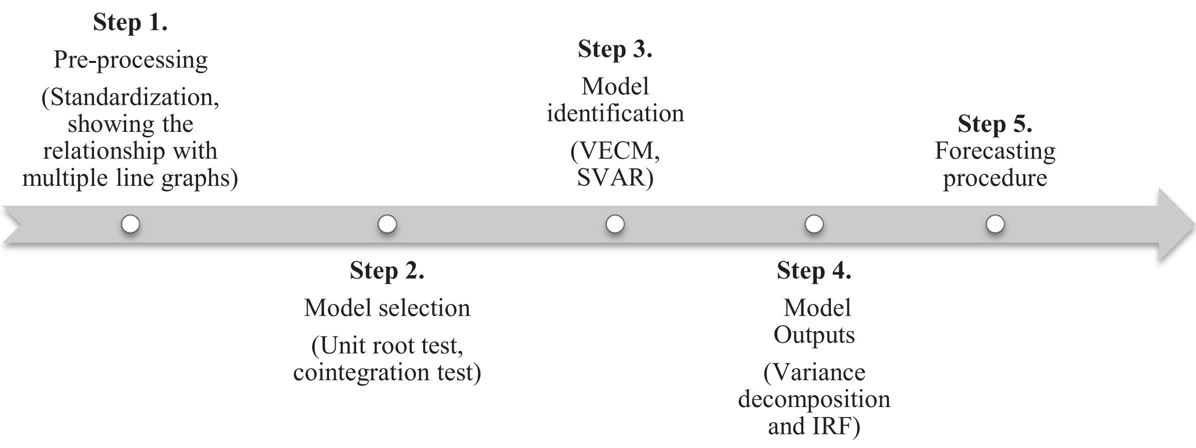

Figure 2: Flowchart of the methodology

recovery period for the CLF under the effect of financial and operational variables the time series is included by monthly data between January 2016 and May 2021. CLF is obtained by dividing CTK into ACTK by including the supply and demand to show the volume. ACTK, CTK, GDP, Domestic, and International Freight Numbers are endogenous variables thought to affect the CLF in time series modeling. The framework of the study is given in Figure 2. As the first step, series are transformed with standardization to avoid variability to interpret the results correctly by extracting the mean and dividing the standard deviation in time series modeling. To implement the proper model unit root and cointegration assumptions are checked. Then the Vector Error Correction Model (VECM) and Structural Vector Autoregressive (SVAR) model results are compared by visualizing impulse response functions. The functions of the impulse response show the relationship between CLF and the other endogenous variable. By considering the significant variable's effect on the endogenous variable, these variables are taken into account as exogenous variables. The variance decomposition

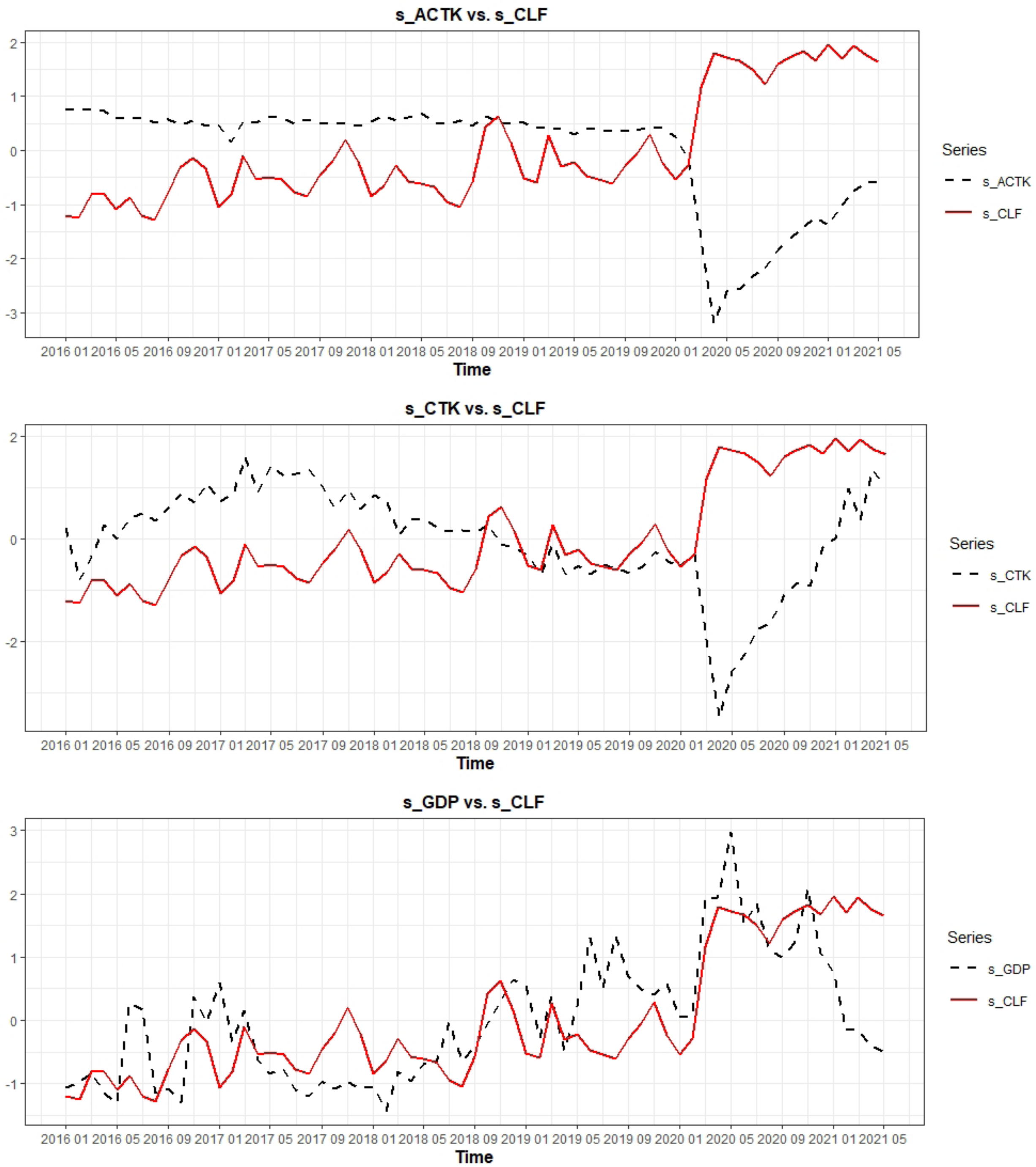

Figure 3: The standardized time series plot comparing s_CLF and s_ACTK s_CTK, s_GDP

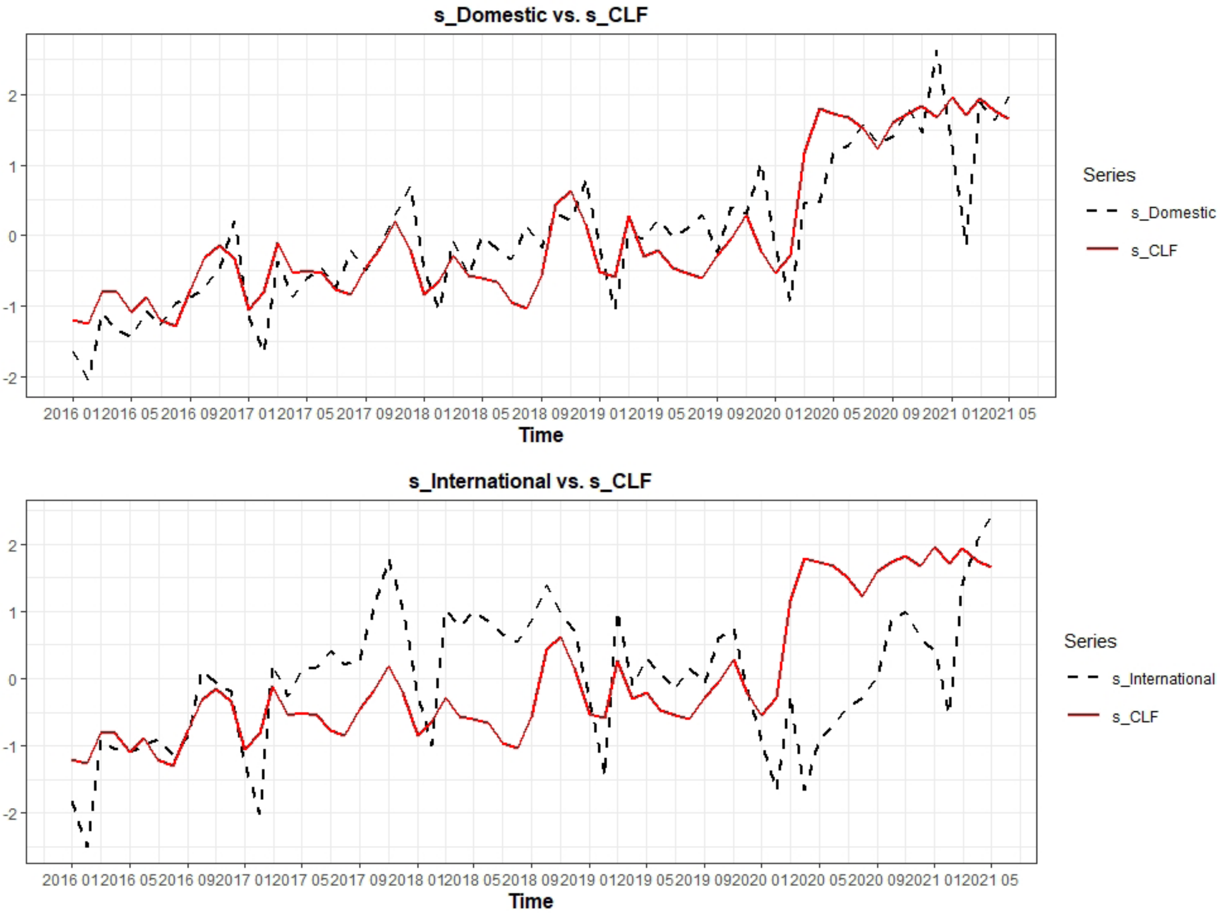

Figure 4: The standardized time series plot comparing s_ACTK and s_Domestic and s_International passengers

is used to show the contribution of the exogenous variables. Finally, the forecasting. The procedure is done to interpret the recovery period. The process explains in detail in the subsections of methodology. The time series analysis conducts in R 4.0.2.: "TSA, vars, forecast, and tsDyn packages" [48].

When the standardized series (Figure 3, and Figure 4) are examined, they can give an idea about stationarity and the relationship of the series.

From January 2016 to May 2021, s_ACTK, s_CLF, s_CTK, and s_GDP variables are shown in Figure 3. It seems a dramatic decrease in April 2020 due to the whole spread of the COVID-19 Pandemic globally in the parameters of s_ACTK, s_CTK, and s_GDP. Although the best increase trend in April and May 2021, s_ACTK was not reached its previous level due to this dramatic decrease that cannot be recovered in one year. However, the s_CTK variable reached the "before COVID-19 numbers" in January 2021 due to the changing trend in the usage of passenger aircraft for freight carriage in terms of occupancy rate, but this trend has not reached the same level in total freight carriage. However, this trend has continued its increasing level from February to May 2021.

From January 2016 to May 2021, s_ACTK, s_Domestic, and s_International variables are shown in Figure 4. It seems a dramatic decrease such as s_ACTK, s_CTK, and s_GDP variables reveal for the domestic, and international freight numbers in April 2020 due to the COVID-19 Pandemic. Afterward, there is an increase in June 2020 due to low capacity usage of freight aircraft, s_CLF values peaked, and this status revealed the unstable trend. So, it understands from this period that s_ACTK and s_CTK show the airfreight trend through the period more properly than CLF due to differences in demand before and after COVID-19. However, this unstable trend changes in the forecast period between July to November 2021. Correspondingly, CLF has a proper variable for showing the trend in the forecasting period (June to November 2021). Because the continuous period of this positive trend shows it is reached the freight numbers before COVID-19.

Unit root test and determining lag-length

The time series analysis has stationary in high precedence. The notion of stationarity and the time series' mean and variance is stable. The covariance between the two series about their values expresses depending on the number of lags of the series. In time series models' application, series must be reduced from trend and seasonality (not changing over time). The nominative method uses to assess stationarity. This method uses Augmented Dickey-Fuller (ADF) test statistics [49; 50]. For resolving the autocorrelation problem, the lags of the dependent series adjoin to the right of the equation. So the test is applied to the ADF test as a new model. Dickey et al. [51] proposed a test based on the problems emerging by autoregressive time series. This test is shown as follows.

$$\Delta y(t) = \alpha + \rho y(t-1) + \beta T + \sum_{s=1}^{p} d_s \Delta y(t-s) + u_t \quad (1)$$

In formula (1), $\Delta y(t)$ is the K-dimensional vector of observed variables. α is the Kx1-dimensional constant vector, t is a time trend, and u_t is the error term which has 0 mean and constant variance called white noise. This test is applied to both levels of the series and their initial differences. The null hypothesis is related to the series below inquiry has a unit root, as opposed to the alternate it doesn't have. In all cases, the lag length is selected by minimizing the final prediction error (FPE) from Akaike [52]. While specifying the appropriate lag length; the Likelihood Ratio Test (LR), Akaike Information Criteria (AIC), Schwarz Information Criteria (SC), and Hannan-Quinn Information Criteria (HQ) can apply. The optimal lag length determines the smallest value in all tests except the LR test. The LR test is found by testing the likelihood ratio statistic, which has an $\chi 2$ structure, at the determined significance level [53].

The cointegration test

After the stationary investigation between the series, the long-term connection between these series is analyzed by the cointegration test. In the literature, three different models use the cointegration test. These are Engle and Granger's [54], Johansen and Juselius's [55], and Pesaran, Shin, and Smith's [56] methods. In this study, Johansen and Juselius [51] are chosen this method since analysis carries out with more than two variables. The null hypothesis (H_0: r=0) is that the series does not have a cointegration vector. The alternative hypothesis (H_0: r≠0) cointegration vector includes the time series [57]. This hypothesis has a cointegration vector (cointegrated series I(r)). r denotes the number of cointegration vectors. Having at least one cointegrated vector in the study means a long-term connection among the model series as these series are stationary in the same order. Since the long-term connection determines this study's stage, the VECM should be included in the model.

Vector error correction model (VECM)

VECM distinguishes the long-term and short-term relationships between series. This model was developed by Engle and Granger [54] to separate the short-term relationships. VECM tries to determine whether the series encounter any shock in the long term. The model establishes to operate the VECM according to Engle and Granger [54] is as follows;

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

Formula (2), $\Delta y(t)$ is the K-dimensional vector of observed variables. α is the Kxr-dimensional coefficient matrix, β is the Kxr dimensional cointegration matrix, Γ_i is the kxk-dimensional short term coefficient matrix and u_t is the error term. It has 0 mean and constant variance called white noise. The error correction parameter (β) keeps the model dynamics in balance and forces the variables to approach the long-term equilibrium value called the Error Correction Term (ECT). Whether the term of error corrections' coefficient is statistically significant, indicates the presence of bias. The coefficient size is a speed indicator of convergence to the long-term equilibrium value. Practically, the error correction parameter anticipates statistically negative significance. In this case, it is stated that the variables will move towards the value of long-term equilibrium. Short-time deviations from equilibrium will be corrected. It is done depending on the dimension of the coefficient about the parameter of error correction. p is the lag order, and the lag-length p in VECM is selected by the maximum lag and minimum Akaike Information Criteria (AIC) [52].

Structural vector autoregressive model (SVAR)

An SVAR model is a structural form of VAR and the structure of the model is as follows:

$$Ay(t) = A_1^* y(t-1) + \cdots + A_p^* y(t-p) + Bu_t \quad (3)$$

In formula (3), u_t is the structural errors that have white noise. The A_i^* for i =1,…,p are coefficient matrices, which are structural coefficients that differ in general from their decreased form counterparts. To determine shocks, the SVAR model can be used by drawing impulse response function graphs by imposing restrictions for A and B. Identifying restrictions are applied to impulse response functions on the SVAR described in Arias et al. [58]. Based on the imposed restrictions, the types of SVAR models are:

A model: B is set to the identity matrix and the number of identification for restrictions is K(K-1)/2.
B model: A is set to the identity matrix and the number of identification for restrictions is K(K-1)/2.
AB model: Restrictions are placed on both matrices and the number of identification for restrictions is K2+K(K-1)/2.

Table 4: ADF test results for evaluating stationarity

Endogenous variables	s_ACTK	s_CTK (1^{st} diff.)	s_CLF (1^{st} diff.)	s_GDP	s_Domestic	s_Inter-national
ADF test value	-1.885	-5.806	-7.304	-2.141	-2.224	-3.284
p	0.003	<0.001	<0.001	0.005	0.003	0.001

Note: *s_ACTK, s_CTK (1st diff.), s_CLF (1st diff.), s_GDP, s_Domestic, s_International*
To determine lag-length AIC, HQ, SC, and FPE tests are considered. In these tests, the optimum lag length is found to be 8 using the VECM model construction for this data set, taking into account the lowest AIC, HQ, SC, and FPE test statistics.

In this study, A model is constructed. The effects of the lagged endogenous variables on the dependent variable are described by the A matrix. A matrix identifies the dynamic relationships between the variables.

Impulse response functions and forecast error variance decomposition

It is hard to explicate the estimated coefficients in VECM. Consequently, to explicate the model outcomes, impulse-response function (IRF) graphs that are graphical statements of the answers related to diversified shocks are applied. The function graphs of the impulse-response are acquired from the vertical axis. The way and size of the answers of other series figure out an increment at the standard deviation reacts to the appropriate series. The shock applies to the horizontal axis for 12 months. Red-dashed lines exemplify ± 2 standard error reliance intervals for the variables' reaction and play a significant part in defining the statistical importance of the outcomes. The lower and upper bands figure out the same sign demonstrating that the reaction is statistically significant at a 95% reliable level. The straight lines in the graphs exemplify the point prediction of the effect-reaction coefficients, and the dashed lines exemplify the confidence intervals. The Forecast Error Variance Decomposition (FEVD) method uses to validate the connection between series. In the VECM model, a particular variable to its shock and the shock from other variables are examined FEVD. FEVD divides the endogenous variable variation inside the component shocks. It allocates the variance of errors in forecasting in a dedicated variable to its genuine shocks and the other variables in the VECM [59].

Forecasting

The forecasts are taken recursively for the levels of the series. Forecasts for VECM are obtained by converting VECM to a VAR (using the VARrep function) in R. VAR model functions such as forecast, are appropriate for VAR models. To forecast or generate impulse responses from a VECM is converted the VECM to its equivalent VAR model representation. This transformation returns the coefficient matrices of the VAR equivalent to the VECM. VECM (lag = p) corresponds to a VAR (lag = p + 1), so if it is provided the new data for a VECM (lag = p), this new data should actually contain p + 1 rows.

RESULTS AND DISCUSSION

Unit root test and determining delay

The unit root of the series determines the null hypothesis. The alternate hypothesis includes the stationary of time series (or trend-stationary). In Table 4, the null hypothesis is declined at the 0.05 significance level for the variables of the number of s_ACTK s_GDP, s_Domestic, and s_International. The first difference between s_CTK and s_CLF is found stationary. Also, in Table 4, the null hypothesis is declined at the 0,05 significance level. There is no constant, and trend included in the unit root test.

The cointegration test

The cointegration test is necessary, where two or more non-stationary time series are integrated. They cannot deviate from equilibrium in the long term, and they can be used as the series in regression estimations for forecasting s_CLF. r demonstrates cointegration equation numbers. The hypothesis is declined because the test statistic is small for r = 2 at the 5 % significance level. Table 5 shows the existence of cointegration. Because of this, VECM was applied.

Table 5: Cointegration test results

Cointegration equation numbers	Test	10pct	5pct	1pct
r<=5	2.91	6.5	8.18	11.65
r<=4	9.74	15.66	17.95	23.52
r<=3	24.20	28.71	31.52	37.22
r<=2	46.18	45.23	48.28	55.43
r<=1	75.24	66.49	70.6	78.87
r<=0	142.46	85.18	90.39	104.2

Note: *Test, 10pct, 5pct, 1pct*

Table 6: Estimated VECM model results (for s_CLF)

Endogenous variables	**Est. (-1) Std. Err.**	**Est. (-2) Std. Err.**	**Est. (-3) Std. Err.**	**Est. (-4)** Std. Err.	**Est. (-5) Std. Err.**	**Est. (-6) Std. Err.**	**Est. (-7) Std. Err.**
s_CTK	0.332* (0.148)	-0.126 0.236	0.453 0.247	1.152*** 0.220	0.829** 0.235	1.099*** 0.221	0.332 0.185
s_ACTK	0.332*** 0.148	0.158 0.447	-2.025*** 0.313	-1.691** 0.419	-1.332** 0.379	-1.898*** 0.420	-0.250 0.381
s_CLF	0.508 0.290	-0.883** 0.248	-1.511*** 0.237	-1.187** 0.324	-0.693 0.342	-1.528*** 0.283	-0.192 0.427
s_GDP	0.075 0.079	-0.128 0.089	0.205* 0.086	0.046 0.084	0.190 0.093	0.545*** 0.119	0.328* 0.108
s_Domestic	-0.124 0.167	-0.282 0.278	0.374 0.386	0.269 0.441	0.191 0.366	0.051 0.247	-0.937** 0.227
s_International	-0.191 0.122	0.340* 0.131	0.103 0.190	0.381 0.253	0.420 0.252	0.601* 0.217	1.005*** 0.216
Sum of squares residual=42.73921							
ECT1= 0.099 (0.053). ECT2= -0.893(0.302)*							

Note: *.p<0.05, *p<0.01, **p<0.001,****p<0.0001*

Vector error correction model (VECM)

In conclusion of the acquired outcomes, a VECM forms with an r = 2 cointegration vector. The lag length of the model is taken at 8 as mentioned before. The suppositions of the model measured in the next outcomes: Since the p-value = 1.000 Portmanteau test (autocorrelation of residues), the null hypothesis cannot be declined. So, there is no autocorrelation between residuals. Heteroskedasticity assumptions check with ARCH Test. The p-value is found 1.000. So, the null hypothesis cannot be declined and an assumption is provided. The normality test is called Jarque-Bera, the p-value is found at 0.051. So, the normality assumption is provided. Hence, the assumptions are all provided. Table 6 shows the estimated VECM outcomes.

Error Correction Term (ECT) determines the return speed to long-run equilibrium. For the long-run relationship to be stable, it is needed ECT1>0, ECT2<0, or at least one of them cannot be equal to 0. According to Table 6, it satisfies the condition for a long-run stable relationship. Because the error correction model is statistically significant and negative, a re-equilibrium will occur s_CLF from long-term balance. When there is a departure from balance, the deviations correct by approximately 89%. To deeply investigate the long-term effects, the impulse-response functions consider in the following section.

Impulse response function

To prove the findings are admitted as reliable, both IRF confidence intervals must keep in the region above (or below) the zero band. Thereupon, the assessments in the research are made solely if the confidence intervals are in the same region. According to VECM's IRF results, the graph on the middle right-hand side shows that s_CLF began to increase after being impacted by its effect for the long-term and then the effect disappears. The graph on the bottom right-hand side shows that s_CLF began to increase after being impacted by s_International for the short-term and then the effect disappeared. In Figure 5, the bottom left graph shows that s_CLF began to increase after being impacted by s_Domestic for the short term and then this effect disappears. According to SVAR's IRF results, the graph on the middle right-hand side shows that s_CLF began to increase after being impacted by its effect for the short-term, and then the effect disappeared. The graph on the bottom right-hand side shows that s_CLF began to increase after being impacted by s_International for the short-term and then the effect disappears.

The graph on the bottom left-hand side in Figure 5 shows that s_CLF began to increase after being impacted by s_Domestic for the short term and then the effect disappears. As a result, both VECM and SVAR models CLF is impacted by International in the short term. The domestic and its impact on CLF are different for the two models in terms of the periods. The effect lasts longer in the VECM model than in the SVAR model.

Forecast error variance decomposition

The effect of independent variables on s_CLF can be viewed by dividing the forecast error variance. The variance decomposition of forecast error is applied to analyze. The series' amendments are caused by their shocks. They are caused also by the other variables. Variance decomposition applies to specify the effect of other series on a shock that forms in any of the series.

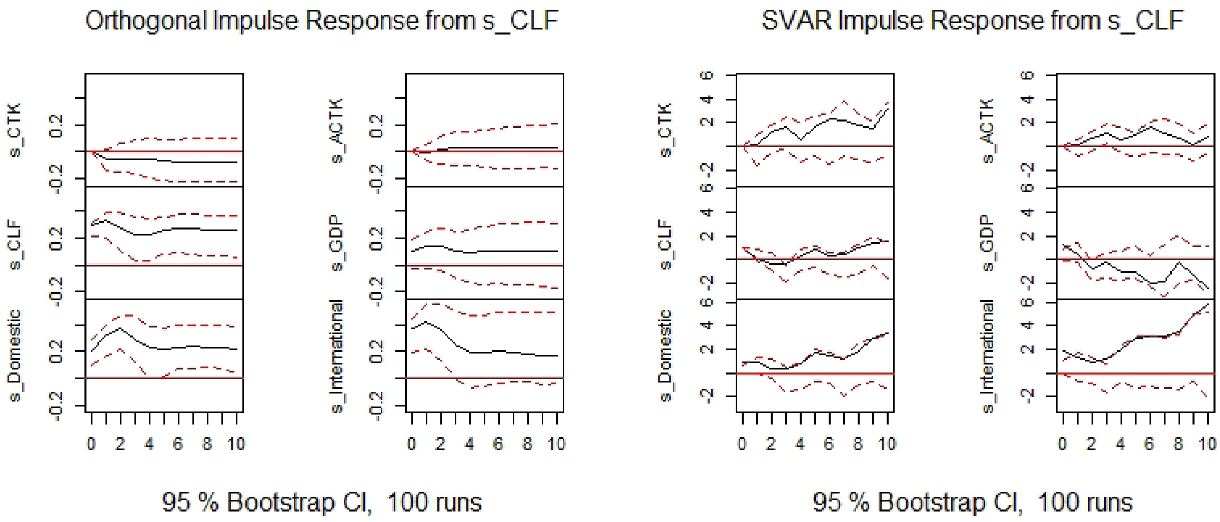

Figure 5: s_CLF impulse response

It describes the amount of percent in a shock unit that comprises one series caused by the amendments in another series.

The FEVD outcomes show that the main variable affecting the s_CLF is interchangeable among s_Domestic and s_CLF by itself about the connection of particular series on the shock in Figure 6. In the short-run effect, the high proportion of variation of s_CLF is explained by s_ACTK and s_CTK. Commonly, the calculation of s_CLF includes these parameters. In addition to Figure 6, the main idea in Figure 5 shows the increase of s_domestic' explained variance on s_CLF.

Forecasting

6-months forecast outcomes are found with the VECM due to considering the IRF results. More proper outcomes will be acquired in the long term. This happens when the value of the s_CLF is advertised for each month and attached to the model. Forecasting outcomes are as follows. According to Figure 7, the

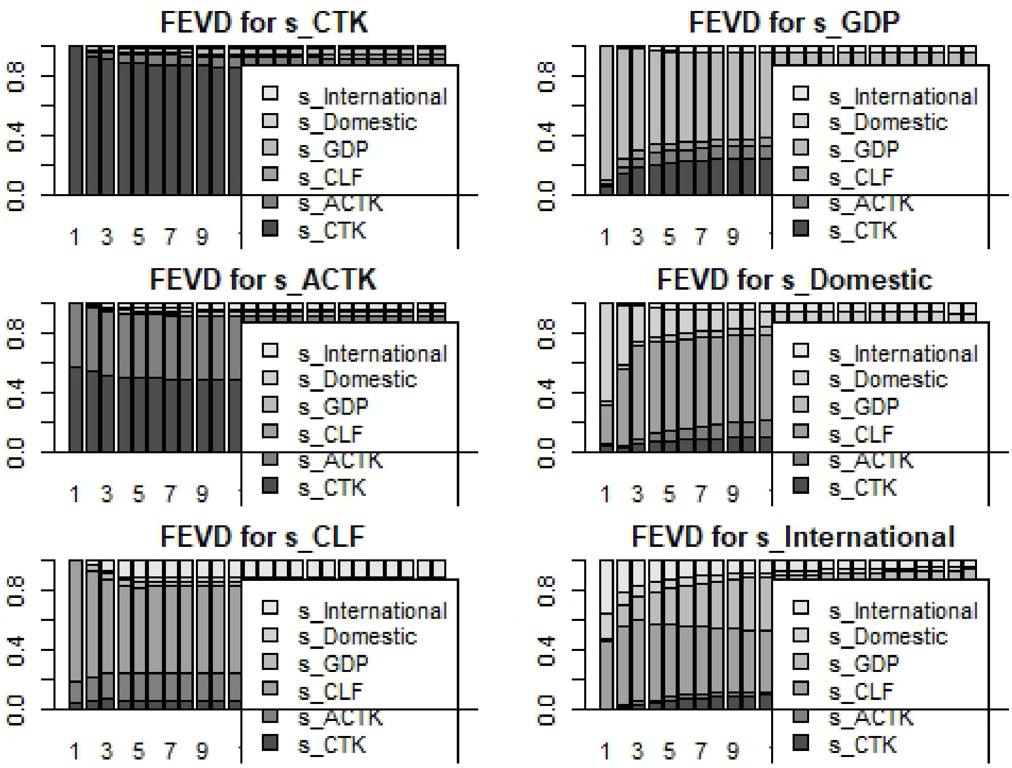

Figure 6: Forecast error variance decomposition

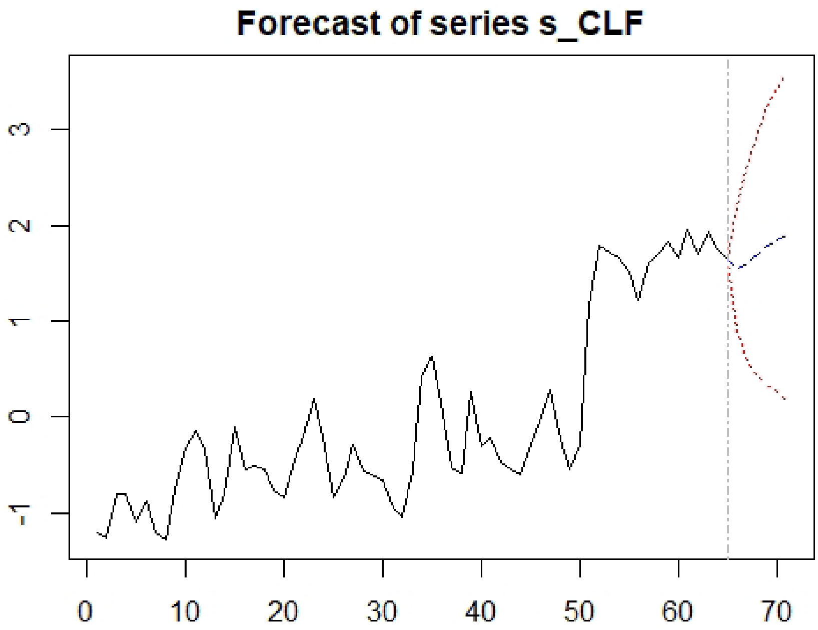

Figure 7: Forecasting of s_CLF

blue line is the conditional forecast, while the red lines are the upper and lower bounds. When the forecasting results figure out with graphs, the s_CLF series is seen to rise after June 2021. In the comparison of the data from June 2019 to November 2019 with June 2018 to November 2018, the trends of CLF are changing between -4.8% to -%1.1. In the comparison of the data from June 2020 to November 2020 with June 2019 to November 2019, the trends of CLF are changing between -17.6% to -6.2%. In the comparison of the data from December 2020 to May 2021 with December 2019 to May 2020, the trends of CLF are changing between -0.5% to %1.2. Correspondingly the last published data shows that the trends of CLF are more than the recovery trend because the revealed numbers are better than before COVID-19. The forecasting period between May 2021 to November 2021 shows that this increasing period will last in the future.

Since model assumptions are provided, the forecasting results can examine. 6-months forecasting is applied for the VECM. The data relies on May 2021 is withal figured out in Table 7 to make a comparison. This model forecasts that the trend will increase better than an unstable trend from the 7th month of 2021. This forecasting model shows the increasing trend. Beginning in July 2021, the increasing rate changes between 0.032 and 0.093 (it examines from June 2021 to show this trend). CLF is taken for the forecasting. Because this variable shows the ratio of CTK/ACTK by including the volume of supply and demand. However, this ratio is not gained by only dividing these two variables. Additionally, supply and demand factors affect GDP level and domestic and international freight numbers. To sum up, CLF shows the total evaluation to analyze how the operation is going as a whole.

Table 7: Forecast values for s_CLF

	Forecast	**95% CI Lower Limit**	**95% CI Upper Limit**
May 2021	1.651	-	-
June 2021	1.549	0.906	2.191
July 2021	1.606	0.578	2.634
August 2021	1.699	0.425	2.974
September 2021	1.786	0.337	3.234
October 2021	1.842	0.266	3.419
November 2021	1.874	0.167	3.581

Note: *Forecast, 95% CI Lower Limit, 95% CI Upper Limit*

CLF also shows the operational success related to the transport volume and financial success by benchmarking the CTK/ACTK ratio. Figures 2, 3, and Table 7 show that the recovery trend started in February 2021 by increasing the transport volume. The financial revenues started to increase in May 2021 with a slightly positive, June 2021 slightly negative, and July 2021 dramatically positive trend. The forecasting values of s_CLF show that the operational and financial continued its positive trend except June 2021 with the starting of July 2021. So in the five months, the increase in financial revenues related to operational success can be observed.

Table 8: Estimated VECM model results (for s_CLF) for testing validity

Variables (lags)	Estimate (Standard Error)	Variables (lags)	Estimate (Standard Error)
s_CLF (-1)	0.6422 (0.1847)**	s_CLF (-2)	0.1338 (0.2232)
s_CTK (-1)	0.1588 (0.1722)	s_CTK (-2)	0.4764 (0.2081)*
s_ACTK (-1)	0.868 (0.1397)	s_ACTK (-2)	0.1797 (0.1688)
s_GDP (-1)	0.1368 (0.2838)	s_GDP(-2)	0.1118 (0.3428)
s_Domestic (-1)	0.6663 (0.2110)**	s_Domestic (-2)	0.3555 (0.2549)
s_International (-1)	1.2210 (0.2569)***	s_International(-2)	0.5706 (0.3103).
Sum of Squared Residuals (SSR)= 42.30186			
ECT1= -0.5694 (0.1593)*** ECT2= 0.0416 (0.0302)			

**p<0.05, **p<0.001, ***p<0.0001*

Validity of the model

In the period from January 2016 to August 2020 (excluding the last 10 months in the previous analysis), the series is used for checking the validity of the model. According to the ADF analysis, the null hypothesis is rejected significantly at the 0.05 level for s_ACTK, s_CLF s_GDP, s_Domestic, s_International. The first difference of s_CTK is found stationary. To determine lag-length AIC, HQ, SC, and FPE tests are considered. The lag-length is found to be 7 in optimum in these tests applying the VECM model for the structure of this data set, but the lag-length number is specified as 2 about the contemplating of the data with a low number in the series' structure. Therefore, the cointegration test is necessary, and it can be used in the series in the estimation of regressions for forecasting s_CLF. The hypothesis is rejected due to the small test statistic for r = 2 at the significance level of 5 %. In the analysis of the acquired outcomes, a VECM was conducted with an r = 2 cointegration vector. The assumptions of the model are provided. Since the p-value = 1.000 Portmanteau test, the null hypothesis cannot be declined. So, the residuals do not correlate. Heteroskedasticity assumptions are checked with ARCH Test. The p-value is found 1.000. So, the null hypothesis cannot be declined and the result provides the assumption. For the long-run relationship to be stable, it is needed ECT1<0, ECT2>0, or at least one of them cannot be equal to 0. The results are is satisfied with the condition for the long-run stable connection. Because the error correction model is statistically significant and negative, a re-equilibrium will occur s_CLF from long-term balance (Table 8). As a result, it can be said that the forecasts with the VECM model are robust and valid.

CONCLUSION

COVID-19 has had an unheard-of long-lasting and negative effect compared to former Pandemics and economic crises. The devastating impact was usually domestic in the former Pandemics. The impact of COVID-19 not only affected countries on the domestic scale. This impact affected countries globally. In the introduction and literature review, general information has been provided on the emergence and spread of COVID-19 by describing the term air freight with its working principle. In the sample of data part, ATK (ACTK), RTK (CTK), LF (CLF), and GDP variables use for national and international freight traffic data in the analysis. This calculation shows the operational and economic status of airlines. It is a forecast done under the air freight transportation data for the last five years and the first five months of 2021. The standardized time series plot includes s_LF and s_ATK, s_RTK, GDP, and national, and international air freight numbers to show figures to describe the relationship between these series in methodology. The analysis aims to forecast the recovery period of airfreight transportation by using the LF (CLF) variable. Despite the decrease in total volume, LF (CLF) expresses ATK (ACTK) in the COVID-19, and the revenue tonne load ratio that defined RTK (CTK) has shown an increasing trend. This growth rate has also increased the total volume of load occupancy rate, which is defined as LF (CLF) after the COVID-19. This increase can be seen as the specialization of airlines in freight transport strategies. The problems that occurred in air transportation resulting from COVID-19 can be fixed by changing the configurations of passenger aircraft to freight transportation in high volumes. Some airlines change the configuration of some of their aircraft by removing seats to carry more volumes of freight, however, some airlines do not change their configuration and carry fewer volumes of freight.

According to forecasting results, it observes that the numbers of airfreight transport have a developing trend in February 2021 in terms of CTK. CTK trend has relatively lower than the getting back into circulation period on February 2021, despite the higher numbers on April and May 2021. When the CLF level decreased in June 2021, the forecast results show that the trend will continue with robust growth. This growth is better than the getting back into circulation period between July to November 2021. This increasing trend explains with the airlines focus on freight transportation and have become more specialized in this field due to the number of passengers that continues to be below 50% compared to 2019. Vaccination has a rising trend globally, especially in passenger transportation, so airfreight transportation also benefits from this growth trend more than passenger circulation. Due to the application of these recent developments in this short-time period, there is not enough research data on the specialization and changing strategies of passenger, combinational, and full cargo airlines in airfreight transportation. It determines the managerial implication of this study is the necessity of airlines to increase their freight operations. The operations managers will need to continue benefiting from this increasing trend in two ways. Firstly, demanding to use passenger aircraft for freight purposes with changing their configurations during the Pandemic period due to the late recovery trend of passenger transportation compared to the freight one. Secondly, giving importance to airfreight transportation more than before the pandemic period by changing the strategies for pricing for different kinds of cargoes suitable for their specifications. Freight transportation has gained importance as a newly developing module of the civil aviation sector during the post-pandemic period. Evaluating this importance will include a specialization process to reduce the economic damage obtained in this troubled period.

The findings show that CLF is affected by itself and domestic transportation in the long-term period. This effect seems as long-term domestic, and short-term international. In other words, a change in domestic transportation affects CLF in the long run, while a short-term change in international transportation effects disappears in the long-term period. The presence of the Delta variant was not available in May 2021. So, the literature review does not include information about the Delta variant. This variant has the potential effect negatively on air passenger transportation more than airfreight. June and July 2021 data' showed the Delta variant not harming airfreight and also air passenger transportation. Despite this variant, The European Organisation for the Safety of Air Navigation, generally named Eurocontrol, shows a positive trend in daily flight data, especially for almost all European Airlines. This positive trend is the same as the other continents with small differences. These data have revealed that air passenger transportation has a positive trend with the aid of the Summer Season, and the statistics show that airfreight transportation has a positive trend more than passenger one [11]. In future studies, air passenger variables can use (by explaining the applied nowadays strategies in air transport) in multidimensional scaling. After the variables are decreased to three factors for showing in a 3D visualization, they can be shown on a map to analyze the yearly status of passenger transportation data. In addition to the forecasting trend by using VECM, the economic welfare and the human development index variables related to the ICAO's regions can also be used in these studies.

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