Using Time Series Analysis Forecast Post-Covid-19 Period Deep Sea Freight Transportation Index

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Abstract. This paper is a study to predict the trend of the Deep Sea Freight Transportation Index after the end of COVID-19 using ETS modeling in the context of the abnormal increase in the Deep Sea Freight Transportation Index due to the COVID-19 epidemic using time series analysis. The purpose of the study is to help international supply chain practitioners and shipping companies to make risk assessments in advance at the decision-making level. In the methodology section, the primary dataset used is the US Deep Sea Freight Transportation Index and the secondary dataset is the WTI Crude Oil Index. The forecast result is that the U.S. Deep Sea Freight Transportation Index will remain high for the next two years, and the WTI Crude Oil Index supports the accuracy of this forecast in its forecast plot based on its correlation with the Deep Sea Freight Transportation Index. Therefore, this study suggests that international supply chain operators and shipping operators should respond to the continued high ocean shipping costs in the next two years to avoid inventory risk and profit decline.

Keywords: Time Series, Deep Sea Freight Transportation, Exponential Smoothing.

1. Introduction

Along with the decrease in efficiency of customs clearance in various countries due to the COVID-19 epidemic in the past three years and the increase in the cost of sanitary decontamination of imported goods in individual countries, the international ocean freight container index has experienced a long cycle of upward ranges. In general, perverse cargo price increases tend to be caused by blockages at key shipping nodes, reductions in freighter schedules for extraordinary reasons such as war, or higher international heavy oil prices. Regarding the first reason, only the 2021 Suez Canal obstruction in the last two years fits its basic characteristics, and this event lasted only six days before and after, so it cannot be considered as a decisive factor for this upward cycle; the latter two factors are met in combination with the changes in international oil prices in recent years and the extended clearance cycle due to the COVID-19 epidemic, respectively reasons [1]. When studying topics related to the international shipping industry, using the U.S. shipping index as a target has the advantage that the U.S., as a bi-oceanic country with a pivotal role in both Atlantic and Pacific shipping, has a better indicator than a specific country in Europe or Asia. Therefore, this study will use the Time Series analysis tool to model fitting and forecast the U.S. maritime transport index and international crude oil prices. Research on this topic will help international suppliers to anticipate supply chain costs in the coming years, and the analysis of abnormal ocean freight indicators in the past three years will help all segments of the international supply chain to make accurate preventive decisions in advance when such a black swan time occurs in the future.

In past related studies, maritime indices have often been studied as part of the overall supply chain analysis; in other studies, the maritime industry analysis has taken a specific port as the basic unit and analyzed its throughput [2]. In the latter category of studies, the use of time series and linear regression analysis to analyze and model the demand for imports and exports is the prevailing direction [3]. In R. Patil and K. Sahu's study of Mumbai port, they constructed linear regression models using GDP and crude oil production as auxiliary indicators to corroborate the port throughput model based on time series analysis [2]. This provides considerable inspiration for the writing of this paper, as the more macroscopic maritime transport indices rely more on auxiliary indicators to assess their forecast results than throughput forecasts. As mentioned in the Background section, the price of crude oil has a considerable influence on the cost of shipping, so it is appropriate to use this indicator as an auxiliary indicator for the study. Existing studies in this area include the analysis of the relationship between crude oil and tanker freight rate using the Cross-correlations approach. In F. Chen et. al's study, the Multifractal Detrended Cross-Correlation Analysis (MF-DCCA) method was used to analyze the West Texas International crude oil (WTI) and Baltic Exchange Dirty Tanker Index (BDTI) using the 2008 international financial crisis as the key time point [4]. The relationship between the West Texas International crude oil (WTI) and Baltic Exchange Dirty Tanker Index (BDTI) is analyzed using Multifractal Detrended Cross-Correlation Analysis (MF-DCCA) [4]. The results of their study show that compressing the sample size of this type of data to a relatively limited interval before and after the crisis can effectively improve the accuracy of the model, and this study will refer to this result for model construction [4].

2. Methodology

2.1 Data Pre-processing

The primary data set used in this study is called *Producer Price Index by Industry: Deep Sea Freight Transportation: Deep Sea Freight Transportation Services*, and the statistical unit is the U.S. Department of Labor [5]. In processing the raw data, several outliers in the dataset were removed first. The data set was then transformed into a time series format by applying the ts() equation from the forecast package and it's time series plot is shown in Fig. 1. The dataset ultimately contains 403 observations in a 12-month cycle. The secondary data set used in this study is the West Texas Intermediate (WTI) crude oil index [6]. Similar to the treatment of the primary dataset, this dataset is also time-serialized using the ts() equation of the forecast package and it's time series plot is shown in Fig. 2.

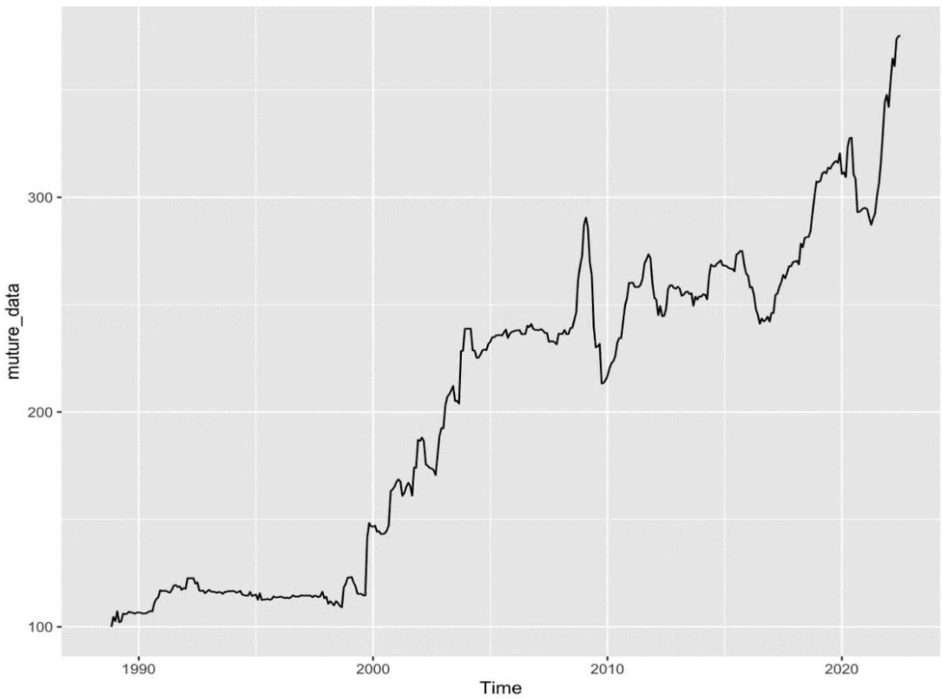


Fig 1. Time series plot of main dataset (Photo Credit: Original)

Fig 2. Time series plot of secondary dataset (Photo Credit: Original)

2.2 Dataset Model Modeling

2.2.1 Main dataset model

After completing the pre-processing of the master dataset, the analysis proceeds to the model building phase. By observing the dataset plot, it can be concluded that this dataset is non-stationary dataset and therefore suitable for Error Trend Seasonal (ETS) model for fitting [7]. The ETS model is mainly used to model Non-stationary data sets, and its basic mathematical principles are:

$$ETS(M,A,N)yT+1=(\ell\mathrm{T}+\mathrm{bT})\times(1+\varepsilon\mathrm{T}+1) \tag{1}$$

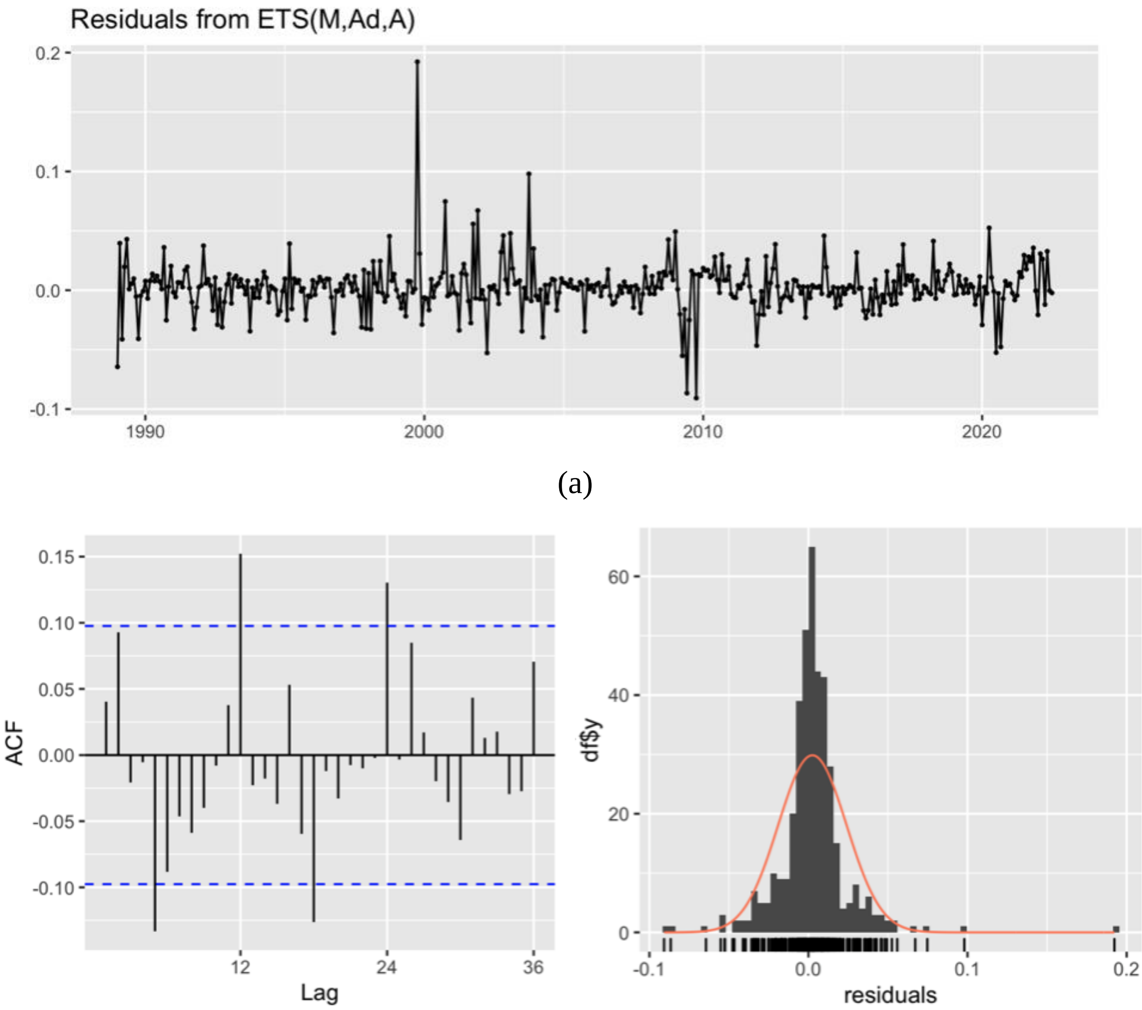
The advantage of using the ETS model is that since the two indices, Akaike's Information Criterion and Bayesian Information Criterion, can be used to select the ETS model, a certain amount of error can be avoided in the model selection phase.

$$AIC=-2\log(L)+2k \tag{2}$$

$$BIC=AIC+k\times[\log(T)-2] \tag{3}$$

Where L indicates the likelihood of the given model and k indicates the total number of parameters and initial states that have been estimated. After the modeling was completed, the p-value of the model was tested by applying the check residual function and the final result was p=0.0003, and the residual image showing white noise in Fig. 3. This points out that the data sampling has a random character and there is no correlation between each observation. The potential trend for the next two years is plotted using the forecast model in the forecast package. The forecast single-point prediction algorithm is:

$$t=T+1,\dots,T+ht=T+1,\dots,T+h, all\ E(t)=0\ for\ t>T_t>T \tag{4}$$



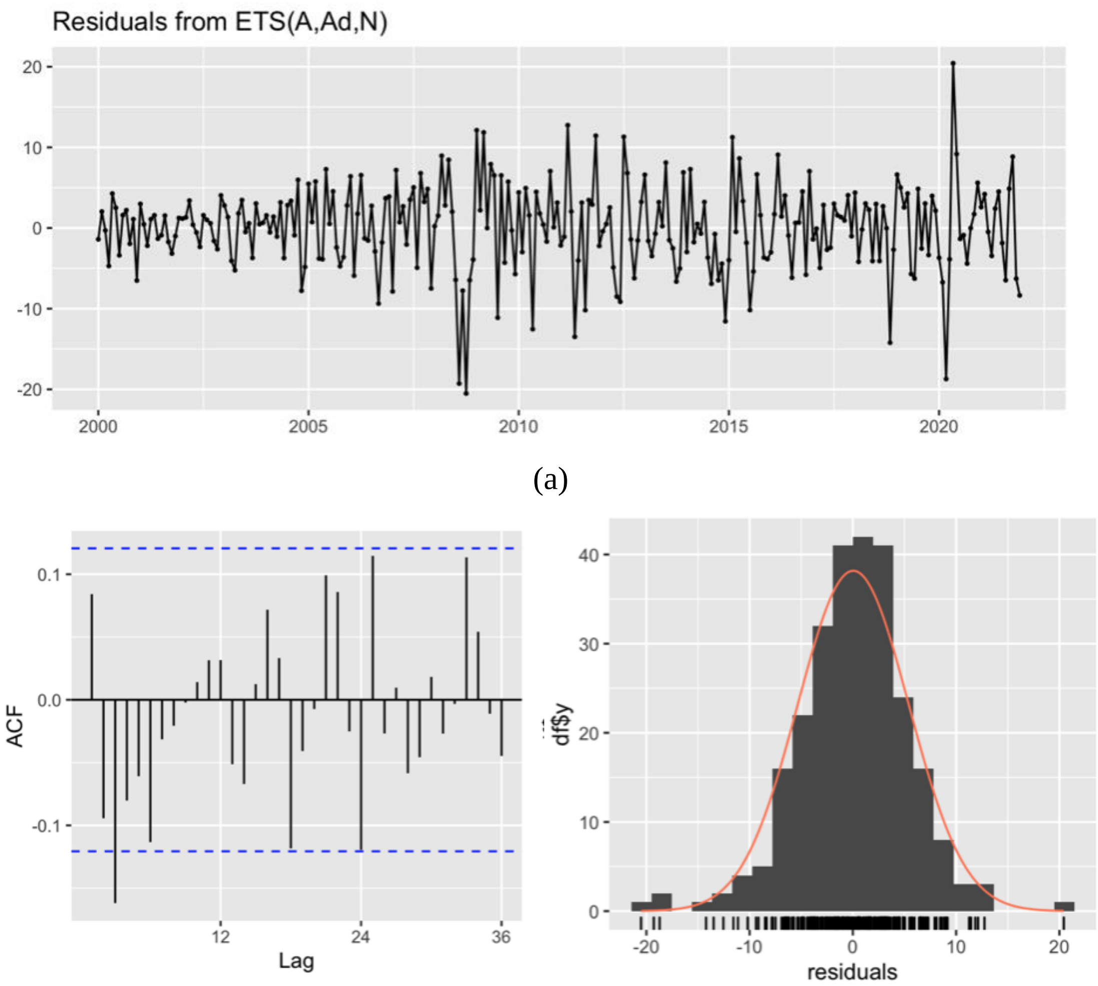
(a)

(b) (c)

Fig 3. Residual testing result of main dataset model (Photo Credit: Original)

2.2.2 Secondary dataset model

After completing the modeling and forecast of the ocean freight indicators, the next step is to model the crude oil index as a secondary indicator. Since its plot also shows a non-stationary trend, it is also modeled using the ETS model. The crude oil index used in this study is the International Monetary Fund's Global price of WTI Crude. after preprocessing, the data interval selected is 2008-2022. Since the data characteristics of the crude oil dataset are highly similar to those of the maritime dataset, a modeling approach similar to the main model will be used in the modeling phase of the crude oil dataset, i.e., the output of the ETS model will be used to compare the AIC and BIC results, and then the best ETS model will be selected and finally the forecast tool will be used to produce the plot output. Similar to the main model, after completing the modeling, the model was tested using checkresidual (), resulting in a p-value of 0.0009 and the residual image showing white noise in Fig. 4. This points out that the data sampling has a random character and there is no correlation between each observation.



(a)

(b) (c)

Fig 4. Residual testing result of secondary dataset model (Photo Credit: Original)

3. Results

After finishing the model training through the experiments in the methodology section, the following results can be obtained by applying the plot derived from the two models using forecast (). First, after the sharp rise in 2020-2021, the shipping index will remain at a more stable high plateau for the next two years, while this interval will show more short-term fluctuations. Second, by comparing the forecasting plots derived from the Deep Sea Transportation index model with those derived from the WTI model, and by combining the conclusions reached by Chen et. al in their study, it can be concluded that the high correlation between ocean shipping costs and crude oil prices leads to the forecasting plot of both showing a high degree of similarity.

3.1 Model Residual Checking Results

Since the dataset of this study is non-stationary dataset, based on the characteristics of this type of dataset, this study does not set test dataset to test the accuracy of the model, but utilizes residual checking to test the p-value value of the model, so as to achieve the test of modeling accuracy. In the test on the primary dataset, the result was p=0.0003; in the test on the secondary dataset, the result was p=0.0009. The model accuracy of both datasets reached the level of 0.001 cutoff point.

3.2 Forecast Plot Interpretation

Fig. 5 is the forecast plot of the Deep Sea Freight Transportation dataset. In this plot, the semi-elliptical interval of the forecast shows a clear scattering feature. This indicates that several outlier points since 2020 have caused considerable disturbance to the model runs; however, since these outlier points represent the large growth intervals since COVID-19 that are of interest to this study, they are not removed from the Methodology stage. However, even though such an interval points to considerable unpredictability, it is still possible to derive a forecast of high index shocks for the next two years from the forecast's curve. Based on the curve changes over the past 2008-2020 years, it can be also seen that such a phase of larger increases will eventually lead to a permanent 25-50 unit increase in the index, a phenomenon that is also likely to occur in the changes beyond 2022.

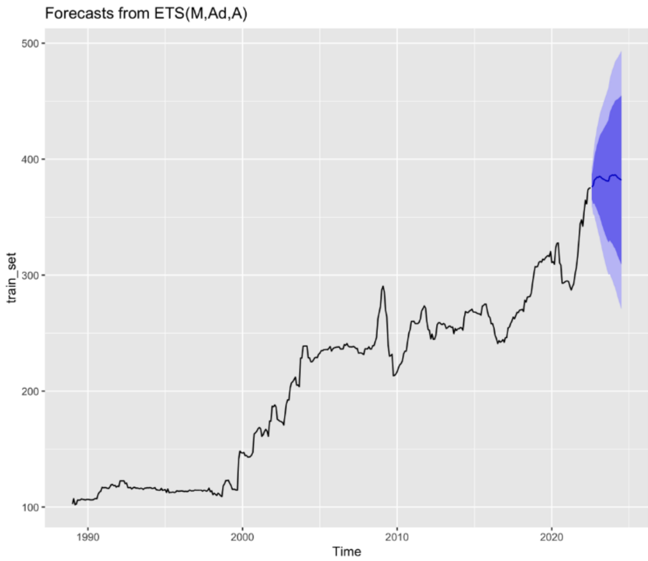


Fig 5. Forecast plot of main dataset model (Photo Credit: Original)

Fig 6. is the interpretation of the forecast plot of the crude oil index. In this plot, similar to the forecast of the shipping index, the forecast of the crude oil index has a large scatter range for the same reason as the shipping index, i.e., there is a large number of outliers in the data after 2020. However, unlike the time series image of the shipping index, the crude oil index experiences a plunge in the first half year of 2020, which is due to the shorting of international crude oil futures in 2020. On the basis of this plunge, the high of the crude oil index in the COVID-19 growth cycle only reached the high of 2018 [5]. On the flip side, the early 2020 plunge that led to the May 2020 production cut of 9.7 million barrels in the Opec countries may have been the main reason for the return to high crude oil prices in the near term; however, the shipping index had the same localized downward trend in the same range in the first half of 2020, and then shot up to all-time highs directly after the crude oil index rebounded, which proves the strong correlation between the two [8].

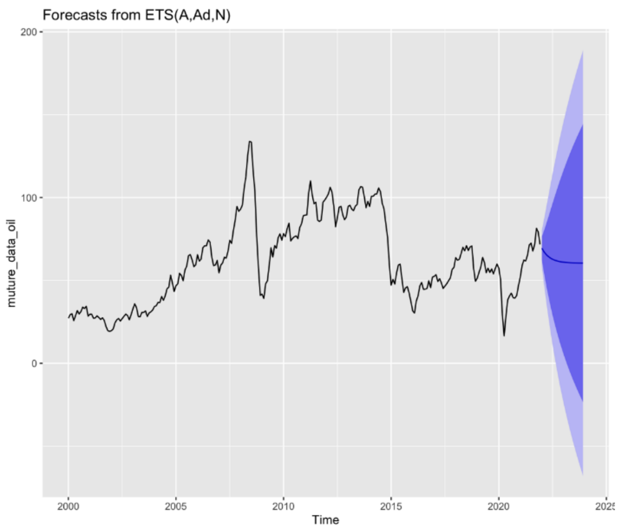


Fig 6. Forecast plot of secondary dataset model (Photo Credit: Original)

In summary, two main experimental results were obtained from this study. The first main experimental result is that the experiment demonstrates from a Time Series perspective that the rise in the Deep Sea Freight transportation index due to a Black Swan event will remain high for the next two years after the end of the upcycle. The second main result is that there is an image level correlation between the crude oil index predicted using the ETS model and the Deep Sea Freight transportation index, and the ETS-based residual plot is highly similar.

4. Discussion

As described in the Introduction section, the findings of this study will help financial or international supply chain practitioners to assess the risk of future black swan events in advance to avoid deepening property losses. By analyzing the time series images over the last two decades, it can be seen that there are two long unexpected growth cycles over the last two decades, from 2008-2010 and 2020-2021. In the theoretical context of economists like Juglar or Kitchin, this situation can be interpreted as an explicit manifestation of the cyclical nature of capitalism, where the market shrinks at the end of the economic cycle after the so-called cyclical production saturation, and this shrinkage forces down the production capacity, including the energy industry, which directly leads to the rise of transportation costs; whether this cycle is 40 months or 9-10 years [9, 10]. The Internet crisis of 2000, the subprime mortgage crisis of 2008 and the COVID-19 crisis of 2020, three seemingly unrelated events, all erupted on the basis of a high level of indiscriminate issuance by national issuing institutions and an overall P/E ratio in the stock market that exceeded parity by tens of times [11]. In contrast, at other points in the three decades between '90 and '20, even if the Crimean crisis or the H1N1 influenza in '09 had a much greater global impact than the three events mentioned above, they did not have a particularly severe international economic impact before or after them.

However, the conclusions reached in this study do not point to the absence of chance in black swan events such as COVID-19. Compared to H1N1 influenza, COVID-19 as a coronavirus has a higher lethality and infectiousness due to its pretype SARS, and the fact that in the first year of the COVID-19 outbreak led to a shift in production of global capacity, indirectly raising supply chain costs in other industries, which is unprecedented in past infectious disease epidemics [12].

Looking back at recent human history, only the 1918 influenza pandemic has had an impact similar to that of COVID-19 in terms of infectious diseases alone. From the economic point of view, the 1918 influenza pandemic hit the rear industries of the warring nations hard, making the war economy of the Second German Empire, which already lacked raw materials, less able to mobilize, and hastening the end of World War I [13]. However, this is not to say that World War I would not have ended without the 1918 influenza pandemic; long before the United States entered the war in 1917, the overall economic and military power of the Allies was already 20% higher than that of the Allies, and the scales of war tipped completely in favor of the Allies after the United States joined the Allies [14]. Based on this view, the 1918 flu in fact only hastened the Allies' defeat, rather than being the main cause of it.

This same logic can be applied to the main topic of this study, which is to forecast the change in the International Ocean Shipping Index over the next two years. That is, one can remove the factor of certain specific events and instead directly attribute the sudden rise to the retaliatory feedback of certain long-term anomalous indicators at a specific point in time. Based on this argument, this study somehow specializes in the importance of the above three events in the time series; if this hypothesis holds true, various business sectors can in fact predict potential future industry crises in advance by using big data modeling in the form of databases, and those black swan events defined as causal factors can in fact only be considered as crisis catalysts for development.

In summary, this hypothesis based on the cyclical nature of capitalism can also be seen as an economic and statistical manifestation of Francis Fukuyama's "end of history" theory; based on the conclusions of this study, this hypothesis will conclude that the Deep Sea Freight Transportation Index will gradually dilute the rising premium in 2020-2021 with inflationary changes after a high plateau in the next two years, and will eventually be seen as parity by the market and gradually dilute the panic [15].

5. Conclusion

Based on the conclusions drawn in the Result section of this study, it can be considered that the research objectives presented in the Introduction section were achieved. At the same time, the Methodology of this study still has imperfect parts, mainly focusing on the modeling of non-stationary dataset. By the assessment given in the Result section, this type of Non-Stationary type dataset is in fact difficult to show the exact trend by modeling with forecast plot. To further enhance the accuracy of the time-series analysis of Non-Stationary datasets, it would be helpful to use Machine Learning to add more auxiliary data to the model. In addition, further interdisciplinary research in this area is necessary, as comparing key Black Swan events in the Deep Sea Freight Transportation Index timeline reveals that the context of these events spans several domains, including public health, finance, and Internet technology. Therefore, the formation of a focused team of experts from multiple fields is necessary for the next study.

Regarding the target group of this study, international supply chain practitioners as well as maritime industry practitioners, it should be noted that the risk management of international supply chain is still in its infancy at present. Unlike traditional financial industries where stocks or futures employ a significant number of actuaries and risk assessors to regularly evaluate the market, and unlike manufacturing companies that have the flexibility to adjust their assembly lines and employee numbers, this area often requires negotiation between the host government and unions to use policies to manage market risk. This approach has lags and is difficult to manage with data. In future research, maritime companies and international supply chain players should set up special data departments to record detailed inbound and outbound data, so as to strengthen the information technology in this field and lay the foundation for further architecture of risk forecasting systems.

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