







RESEARCH ARTICLE

Financial implications of the COVID-19 pandemic on the container ship time charter business

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ABSTRACT

This study examines the financial implications of the COVID-19 pandemic on the container ship time charter business. In this context, the container charter transactions were derived from the Clarksons Research Database, which included the ship types, daily charter fees, ship ages, and total charter days. The empirical analysis employed the K-Means Algorithm to cluster the observations in which the elbow curves revealed three cluster centers in the pre-COVID period and four in the post-COVID era, respectively. Based on the industry-wide used threshold definitions, the clusters were then named according to the mean value of given features. In addition, the relative weight of each cluster was disclosed based on the number of transactions falling into the respective cluster. Accordingly, the pre-COVID period clusters were described as intermediate-rated middletermed young-aged intermediate-TEU container ships; low-rated middle-termed middleaged feeders; and intermediate-rated long-termed middle-aged upper intermediate-TEU container ships. As for the post-COVID era, the cluster definitions were determined as intermediate-rated middle-termed young-aged feeders; intermediate-rated middle-termed old-aged feeders; high-rated long-termed middle-aged intermediate-TEU container ships; and high-rated short-termed middle-aged intermediate-TEU container ships. The findings suggested that the pandemic boosted the demand for relatively lower TEU container ships such as the feeders in which the criterium of ship age lost its importance due to availability reasons in the market. In addition, the pandemic led to higher charter rates which was a prioritized factor over the charter period.

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Introduction

The socio-economic effects of the COVID-19 virus, which was seen only as a threat to health when it first appeared, reached much greater dimensions all over the world. The COVID-19 pandemic, which was declared by the World Health Organization on March 11, 2020, continued more than 2 years. The effects of the global decline in economic activity as a result of the pandemic on supply chains and international transport are still being felt (Gençer, 2022). A large part of world trade is carried out by maritime transport. More than 50% of maritime transport in terms of the value of cargo is carried out by container shipping (Clarksons Research, 2021). Container shipping is one of the most preferred transport types in international trade, thanks to the safe and intermodal transport opportunities it provides. It can be said that the most important fact in container shipping during the COVID-19 pandemic period is the excessively rising freight rates. In Figure 1, it is seen that the daily rates and earnings of container ships have increased clearly compared to the beginning of the pandemic. Clarksons Container Ship Time Based Chartering Index reached 400, Clarksons Average Container Ship daily earnings approaching 80000 USD (United States Dollar). Similarly, as seen in Figure 2, the Shanghai Container Freight Index reached its highest levels since its establishment in 2009.

Fluctuations in freight rates affect the profitability liner carriers. Therefore, liner carriers may prefer charter ships on time charter basis instead of buying ships, as they cannot foresee how the freight will progress in the future (Munim, 2022).







Figure 2. Shanghai container freight index



Although large ships provide economies of scale, they can carry high risks due to high operating costs, especially when freight rates are low. On the other hand, smaller ships such as feeders can be easily adapted to the region and market in which they operate. These types of ships are less affected by the fluctuations in the industry, as they can also carry other types of cargo besides containers, such as project cargoes. Considering that the use of feeder type ships as general cargo ships is preferred during the pandemic period, when there is a shortage of containers, it is better understood why the demand for this type of ships has increased.

This study examines the financial implications of the COVID-19 pandemic on the container ship time charter business. In this context, the container charter transactions were derived from the Clarksons Database from January 2018 to October 2021, which included the ship types according to their size in terms of TEU, daily charter fees, ship ages, and total charter days.

Literature Review

Due to the COVID-19 pandemic, global supply chains have faced various disruptions due to government restrictions, limited working hours, delayed shipments due to limited staff shortages, longer transit times, shortages of raw materials. During this period, many logistics companies, especially ship owners, operators and ports, sought ways to increase their operational efficiency and global competitiveness (Noteboom et al., 2021). However, the expected impact at the beginning of the pandemic was not as great as feared and the maritime transport sector managed to get out of the crisis (UNCTAD, 2021). In addition, despite all the interruptions and disruptions, maritime transport has once again demonstrated its importance and flexibility by ensuring the continuity of the supply of food, medical products and basic materials (Charbonnaux et al., 2020; Weerth, 2020).

Nowinska & Schramm (2021) examined more than 2700 ship chartering deals in container shipping industry. Their study reveals important findings for decision makers in an environment of uncertainty in the sector. Guerrero et al. (2022) examined the effects of the COVID-19 pandemic on container shipping routes and connections between ports. Researchers have shown a reduction in global seaway connections, demonstrating that large ports and densely interconnected smaller ports are better able to resist the pandemic. Jin et al. (2022) investigated China's international regular container line transport connections during the pandemic period. In the study, it was stated that there were large fluctuations in freight flows, especially between China and the USA, and it was revealed that China's international regular container line transport connections increased even though the number of main ports frequented by ships decreased.

In the literature, there are various studies on the estimation of freight rates and charter rates in maritime transport depending on crisis situations. Munim (2022) proposed Seasonal Autoregressive Integrated Moving Average (SARIMA), Seasonal Neural Network Autoregression (SNNAR) and the state-space TBATS models for forecasting container freight rates. It has been seen that the results of the models can provide promising predictions. Monge (2022), Monge covered the analysis of the evolution of international trade after COVID-19 by examining the shipping industry and the impact of bunker fuel cost. Mo et al. (2022) proposed a neural network model for the prediction of monthly time charter rates of dry bulk ships. The empirical findings of their study show that the model is significant in estimating the shortterm time charter rates. Saeed et al. (2023) introduced the Prophet model for estimating container freights, taking into account the factors of congestion, peak demand, policy, price up, overcapacity and coronavirus. Their study reveals that the proposed forecasting model will help policy makers and practitioners to implement strategies to reduce the risks associated with the variability of freight rates and supply chain costs.

In the time charter rates, period of the charter, the state of the industry and characteristics of the ships come to the fore. In the literature, no study has yet been found on the clustering of container ships according to the characteristics of time charter contract.

Material and Methods

The dataset used in this study was acquired from the Clarksons Database which is the global provider of shipping and sea trade data (Clarksons Research, 2021). The dataset encompassed the charter container ship data for the period between the beginning of 2018 and October 2021, which described the charter date, ship name, built year, capacity in TEU (twenty-foot equivalent unit), charterer description, laycan date, length of the charter period, the daily charter rate in USD and the ship owner, respectively. In the instances where the charter time was presented in a continuous period, such as 9-12 months, the upper bound was taken as the respective value and all values were converted into days. Whereas the total data accounted for 7,174 observations, 624 of them were eliminated



due to missing daily rate values. Hence, the final dataset consisted of 6,550 observations. The dataset was then divided into two sub-groups to represent the pre-COVID and post-COVID periods. The key date for the split was taken as 31.12.2019 in which December 2019 corresponded to the acknowledgment of the outbreak in China.

As for the first step, exploratory data analysis was carried out to investigate the descriptive statistics in both periods to gain insights comparatively. Accordingly, daily charter fees, ship ages, and total charter days were analyzed by container ship types. The container ship types were classified into six groups in the dataset based on TEU capacity thresholds, which were between 100-999; 1,000-1,999; 2,000-2,999; Narrow Beam 3,000+; Wide Beam 3,000-5,999; and 6,000+ TEU, respectively. While carrying out the visual analysis, boxplots were used. Boxplots, often called as the five-number summary, depict the minimum value, the maximum value, the median, and the first and third quartiles that reveal the variability in a distribution. The box in the plot represents 50% of the observations in a distribution where the line in the box is the median. The points below or above the whiskers (lines stretching out the box) are potential outliers that are beyond the 1.5 interquartile range (Agresti & Franklin, 2013). Figures 3 and 4 presented below display the boxplots of daily charter fees by fixture types in the pre-COVID and post-COVID periods.



Figure 3. Boxplot of daily charter fees (USD) by container ship fixture types in the pre-COVID period



Figure 4. Boxplot of daily charter fees (USD) by container ship fixture types in the post-COVID period



The comparison of the boxplots in Figures 3 and 4 revealed that the median of the daily charter rates increased for almost all container ship types in the post-COVID period compared to the pre-COVID time which was comparatively more evident in container ships with larger TEU. In addition, the average daily charter rates increased by 24% (100-999 TEU); 30% (1,000-1,999 TEU); 47% (2,000-2,999 TEU); 90% (Narrow Beam 3,000+ TEU); 49% (Wide Beam 3,000-5,999 TEU) and 44% (6,000+ TEU) between the two periods. Looking at the point observations stretching out the whiskers, it can be concluded that the number of outliers increased in the post-COVID period. Indeed, the variability in the distributions rose in the post-COVID period. Apart from the rise in the daily charter fees, it can be asserted that shipping companies had to incur higher charter costs in particular instances which could be a result of instant urgent demand. The visual analysis continued

with the ship ages by fixture types, which are illustrated in Figures 5 and 6.

The average ship age in the pre-COVID period varied from 11 to 13 years, whereas the variation was between 12 to 16 years in the post-COVID period. The average ship age rose by 9% (100-999 TEU); 20% (1,000-1,999 TEU); 12% (2,000-2,999 TEU); 17% (Narrow Beam 3,000+ TEU); 14% (Wide Beam 3,000-5,999 TEU) and 18% (6,000+ TEU) between the two periods. Given that no new ships were introduced and no others retired, the increase in the average ship age would be expected as a percentage between 8% to 10% due to normal aging. However, the increase rates stated above suggest a higher variation. This could be explained by the increased demand for charter ships in the post-COVID period in which the ship age factor played a comparatively lower role.



Figure 5. Boxplot of ship age by container ship fixture types in the pre-COVID period





Figure 6. Boxplot of ship age by container ship fixture types in the post-COVID period







Figure 7. Boxplot of charter days by container ship fixture types in the pre-COVID period





Thirdly, the charter days by container fixture types are compared in the pre-COVID and post-COVID periods, respectively. The boxplots in Figures 7 and 8 depict this analysis.

The average charter days rose significantly in the post-COVID period for all container ship fixture types substantially. The rate of increase was 51% (100-999 TEU); 36% (1,000-1,999 TEU); 65% (2,000-2,999 TEU); 122% (Narrow Beam 3,000+ TEU); 89% (Wide Beam 3,000-5,999 TEU) and 120% (6,000+ TEU) between the two periods. In addition, the variability in the charter days for all fixture types increased considerably in the post-COVID period. Overall, it can be suggested that the duration of the charter period rose and fluctuated following the outburst of the pandemic.

When it comes to the empirical analysis that was carried out in this study, the applied method was clustering. Clustering encompasses the grouping of data into classes in which those grouped are similar to each other and dissimilar from the rest of the classes based on given qualities. In other words, clustering algorithms detect and group the observations that are similar to each other compared to the rest of the groups (Jayashree & Chithambaramani, 2020). In addition, clustering methods do not require a target or dependent variable. Hence, the number of the groups is defined at the beginning of the analysis, stays constant and the observations are grouped under the previously set number of clusters (Rather & Bala, 2020). Widely used in knowledge discovery in empirical research, clustering methods have evolved into numerous different models in which we can detect publications with more than a hundred diverse clustering algorithms in the literature (Rather & Bala, 2020). Among different clustering algorithms, the K-Means algorithm is a widely used clustering method in which



clusters are classified by their centroids that implies the average value of given observations. The algorithm has an iterative approach in which the predetermined number of cluster centers initially emerge at random, and the recalculation goes on as long as the error function no longer decreases (HajKacem, et al., 2019; Chander, 2020; Giordani et al., 2020). Since the number of clusters is not initially known, the elbow method can be applied to determine the number of clusters. In this method, the within-cluster sum of squares is plotted against the number of clusters. Accordingly, the point at which the elbows vanish leading to a considerable decline in the within-cluster sum of squares can be offered as the number of clusters to be integrated into the K-Means algorithm (Giordani et al., 2020).

Results

The empirical analysis started with the determination of the number of clusters in the pre-COVID and post-COVID datasets, respectively. In this sense, the elbow curve for the pre-COVID period observations depicted the first bump with 3 clusters. On the other hand, the first bump appeared with 4 clusters in the post-COVID observations plot. The elbow curves are illustrated in Figures 9 and 10.

The execution of the K-Means algorithm on the pre-COVID observations classified 38.6% of the observations in the first, 52.5% in the second, and 8.9% in the third cluster. As for the post-COVID period, the percentage of the observations that fell into four different clusters was 30.1%, 55.7%, 13.3%, and 0.8%, respectively. Besides the number of observations corresponding to each cluster, the cluster characteristics were revealed by the mean value of given features in each cluster. The mean values of TEU, daily rate, days, and age for each cluster in the pre-COVID and post-COVID periods are summarized in Table 1 and Table 2.

To define the clusters, the mean value for each feature was compared with the generally accepted industry-standard classifications. As for container ship classes, the TEU is grouped as a feeder (up to 3000 TEU); intermediate-TEU (between 3,000 and 6,000 TEU); upper intermediate-TEU (between 6,000 and 8,000 TEU); neo-panamax (between 8,000 and 12,000 TEU); upper neo-panamax (between 12,000 and 17,000 TEU); and post-panamax (from 17,000 TEU onwards). Daily rates per day (USD) are classified as low-rate; intermediate-rate; and highrate based on the thresholds of up to 10,000 USD; between 10,000 and 25,000 USD; and more than 25,000 USD, respectively. Charter days fall into three categories which are short-term; middle-term; and long-term with up to 180 days; 180-360 days; and more than 360 days. Lastly, ship age can be summarized into three groups which are young-age (up to 10 years); middle-age (between 10 and 15 years); and old-age (from 15 years onwards). In light of the industry definitions and







cluster centers, the first pre-COVID cluster was defined as intermediate-rated middle-termed young-aged intermediate-TEU container ships. The second cluster in this period was lowrated middle-termed middle-aged feeders. The third cluster was intermediate-rated long-termed middle-aged upper intermediate-TEU container ships. On the other hand, when it came to the post-COVID period, the first cluster was intermediate-rated middle-termed young-aged feeders. Secondly, we had intermediate-rated middle-termed old-aged feeders. As for the third cluster, high-rated long-termed middle-aged intermediate-TEU container ships were described. As for the last cluster, high-rated short-termed middle-aged intermediate-TEU container ships were named. The definitions of the clusters including the weight of the observations in each cluster for each period are summarized in Table 3 and Table 4.

Table 1. Mean value of features by clusters, pre-COVID period

Cluster Label	TEU	Daily Rate	Days	Age		
0	3,074.53	11,075.69	229.14	7.99		
1	1,958.26	8,338.39	186.29	14.09		
2	7,435.07	19,708.42	508.24	11.32		
Table 1. Mean value of features by clusters, post-COVID period						
Cluster Label	TEU	Daily Rate	Days	Age		
0	2,519.26	11,693.20	267.61	8.29		
1	1,923.96	10,495.97	273.84	15.71		
2	5,441.83	30,466.06	1,106.71	12.47		

Table 2. Definition and weight of pre-COVID clusters

Cluster Label	Cluster Weight	Definition
0	38.6%	Intermediate-TEU
		Intermediate-Rate
		Middle-Term
		Young-Age
1	52.5%	Feeder
		Low-Rate
		Middle-Term
		Middle-Age
2	8.9%	Upper Intermediate-
		TEU
		Intermediate-Rate
		Long-Term
		Middle-Age

Table 3. Definition and weight of post-COVID clusters

Cluster Label	Cluster Weight	Definition
0	30.1%	Feeder
		Intermediate-Rate
		Middle-Term
		Young-Age
1	55.7%	Feeder
		Intermediate-Rate
		Middle-Term
		Old-Age
2	13.3%	Intermediate-TEU
		High-Rate
		Long-Term
		Middle-Age
3	0.8%	Intermediate-TEU
		High-Rate
		Short-Term
		Middle-Age

Discussion and Conclusion

This study examined the changing trends in the time charter business of container ships due to the COVID-19 pandemic from the financial perspective. The charter instances in the pre-COVID and post-COVID periods were clustered considering the capacity in terms of TEU, daily charter rates, charter period, and the age of the container ships. By using the generally accepted industry descriptions, the revealed clusters were defined and compared with each other in two periods to provide insights into the implications of the pandemic on the industry. Accordingly, the comparison of the defined clusters disclosed the following findings. Firstly, whereas three main container ship classes were observed in the pre-COVID period, this observation was dropped to two in the post-COVID period. The feeders, for which the weight of the instances was 52.5% in the pre-COVID period rose to 85.6% in the post-COVID period. The weight of the charter instances of intermediate-TEU ships fell from 38.6% to 14.2% in the post-COVID period. In addition, the clusters in the post-COVID period did not include upper intermediate-TEU ships which were 8.9% in the pre-COVID period. The increase in the demand for relatively lower TEU container ships can be explained by their comparatively higher availability and relatively lower operating costs in an uncertain economic environment. Secondly, as for the daily charter rates of container ships, the low-rate cluster which dominated the market with 52.5% vanished in the post-COVID period. Indeed, the post-COVID period resulted in the emergence of high-rate charter fees which was not the case in the pre-COVID period. The weight of the intermediate-rate





charter instances rose considerably from 38.6% to 85.8% in the post-COVID period. Hence, the pandemic resulted in higher charter rates in the industry, which can be mainly due to increased demand for container shipping. Thirdly, as for the charter periods, it can be stated that the middle-term charter period, which was the common practice in the pre-COVID period seemed to have lost its weight in favor of long and short charter periods in the post-COVID periods. Considering the daily rates and the charter periods of the clusters together, it can be asserted that container shipping companies had a preference of daily rates or income over the charter period. Lastly, the analysis of ship age showed that the old-age class ships dominated the market with 55.7% in the post-COVID period, which was not observed in the clusters of the pre-COVID period. In addition, the ship type of this class was feeders. Apart from the availability of the feeders, this follows that the ship age seemed to have played a minor role in the charter decisions in the post-COVID era in which the clients opted for what was available in the market.

During the pandemic period, global container liner carriers made frequent changes to their mother ships' schedules, canceling some hub port calls and making calls to other unplanned ports when necessary. In particular, it can be said again that there is not much competition on the main routes where the global container liner carriers, united in the form of alliances, determine the freights and ship schedules (Gençer, 2022; Ksciuk et al., 2023). Accordingly, this study reveals that one of the main competitive elements that make a difference in container shipping is the smaller ships operating in regional transportation.

Smaller ships such as feeders can be easily adapted to the region and market in which they operate. These types of ships are less affected by the fluctuations in the industry, as they can also carry other types of cargo besides containers, such as project cargoes. Considering that the use of feeder type ships as general cargo ships is preferred during the pandemic period, when there is a shortage of containers, it is better understood why the demand for this type of ships has increased.

Future Research

Clustering approach, which is considered in this study, is a very useful method for the rapid and efficient identification, analysis and determination of the current needs of the maritime industry during fluctuations or crisis periods. Therefore, it can be applied to different ship types and can be used as an important decision-making method regarding what size, age and characteristics of ships are in demand, depending on the situation in the industry. In addition, it can also be used to shape the ship portfolios of companies with fleets of different ship types. Nevertheless, due to the largeness, diversity and complexity of the maritime industry, keeping track of all developments and collecting data can be challenging. Therefore, as new data come in the coming periods, there will be much more research in the maritime industry.

Compliance With Ethical Standards

Authors' Contributions

HG: Designed the study, Wrote the literature review, Analyzed the results.

TT: Conducted statistical analyses, Analyzed the results. Both authors read and approved the final manuscript.

Conflict of Interest

The authors declare that there is no conflict of interest.

Ethical Approval

For this type of study, formal consent is not required.

Data Availability Statements

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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