UNIVERSITY OF GOTHENBURG

SCHOOL OF BUSINESS, ECONOMICS AND LAW

Master Degree Project in Logistics and Transport Management

A time series analysis of the impact of the COVID-19 pandemic on container shipping freight rates: An application to the Asia-Europe trade route

Spring 2022

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Abstract

The outbreak of the COVID-19 pandemic caused a sudden disruption to the shipping industry. However, for container shipping, freight rates have reached record highs during the pandemic. Shipping companies realise that understanding the impact of exogenous shocks on freight rate fluctuations to forecast freight rates is critical. Current studies on the correlation between shipping freight rates and the COVID-19 pandemic have usually concentrated on the dry bulk and tanker segments. In order to fill the research gap, this study focuses on how container shipping freight rates on the most dominant shipping routes, the Asia to Europe trade lane, react to the COVID-19 pandemic. Using weekly data from recent years (January 2, 2015 to October 8, 2021), including the period of the COVID-19 pandemic, the GARCH (1,1) model is applied to investigate whether the pandemic and the macroeconomic environment during this period will lead to fluctuations in container shipping freight rates, and to measure the extent to which these variables affect container shipping freight rates. The main findings of this study are 1) the pandemic outbreak has a significant and positive association with container shipping freight rates, 2) the stock market price that causes short-term fluctuations in shipping demand has a strong positive relationship with container shipping freight rates, and 3) for container shipping, the oil price does not exhibit any significant relationship with freight rates.

Keywords: Container shipping; Freight rates; COVID-19; Oil prices; Stock market prices; Time series model; GARCH

Acknowledgements

We would like to express our gratitude to our supervisor, Kevin Cullinane, for his constructive suggestions and deep insights into this thesis. We could not have undertaken this journey without his assistance in acquiring the data and his guidance throughout the thesis. We would also like to acknowledge Lydia Yang, who provided us with valuable comments on this thesis.

Most importantly, we would like to extend our sincere thanks to our family for their support and encouragement throughout the years of our study.

Gothenburg, 27 May, 2022

Yuchun Chen & Shiyu Zhou

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1. Introduction

1.1 Background

The COVID-19 pandemic has spread all over the world since January 2020. At the beginning of the pandemic, governments around the world have adopted control measures to prevent the outbreak of coronavirus disease, which had a negative impact on export trade, especially the lockdown of factories in China (Michail & Melas, 2020; Xu et al., 2021). As a form of transportation accounting for 80% of the global trade, the shipping industry showed a downturn due to the reduction of international trade. In addition, since most manufactured goods are shipped in containers, and China is a major producer of manufactured goods, the outbreak of the pandemic should have a particularly large impact on the container shipping market (UNCTAD, 2021a).

However, the Chinese economy has recovered rapidly from lockdown in 2020, and the demand for Chinese products in Europe and the US has increased because of the e-commerce and festive seasons, while the demand for Europe and the US cargo from Asia is less, which has caused a mismatch of export and import between Asia and the western. The unbalance of imports and exports between Asia and the western has disrupted container flows, leading to an acute container shortage in Asia. Furthermore, empty containers need to be transported from the western to Asia, but carriers are unwilling to do so due to the high cost, adding to the container shortage in Asia. The shortage of containers eventually leads to a high rise in container shipping freight rates (Leng, 2021). From exploring the Shanghai Containerized Freight Index (SCFI) on the Shanghai to Europe trade route (See Figure 1), this could be a sharp increase in the SCFI shown between November 2, 2020 and January 2, 2021. Changes in consumption patterns triggered by the pandemic have made the demand for container shipping rebound rapidly from the slowdown. Massive stimulus packages, along with the growth of e-commerce, have increased consumer spending on goods (UNCTAD, 2021b; McKinsey, 2022). Furthermore, advanced regions have shown optimism due to vaccine rollouts, also partly from unlocking pent-up demand for cars and restocking and inventory-building (UNCTAD, 2021b).

In addition to the shortage of containers during the pandemic, the Suez Canal obstruction in March 2021 has caused freight rates to rise sharply (UNCTAD, 2021a), as shown in Figure 1 between April 2, 2021 and August 2, 2021. The large container ship Ever Given, which can carry 20,000 TEU of cargo, blocked the Suez Canal for a week, causing delays for ships heading to Europe and increasing restrictions on ship and port capacity. Some voyages had to be diverted through the Cape with longer route distances (UNCTAD, 2021b). These all make freight rates increase significantly.

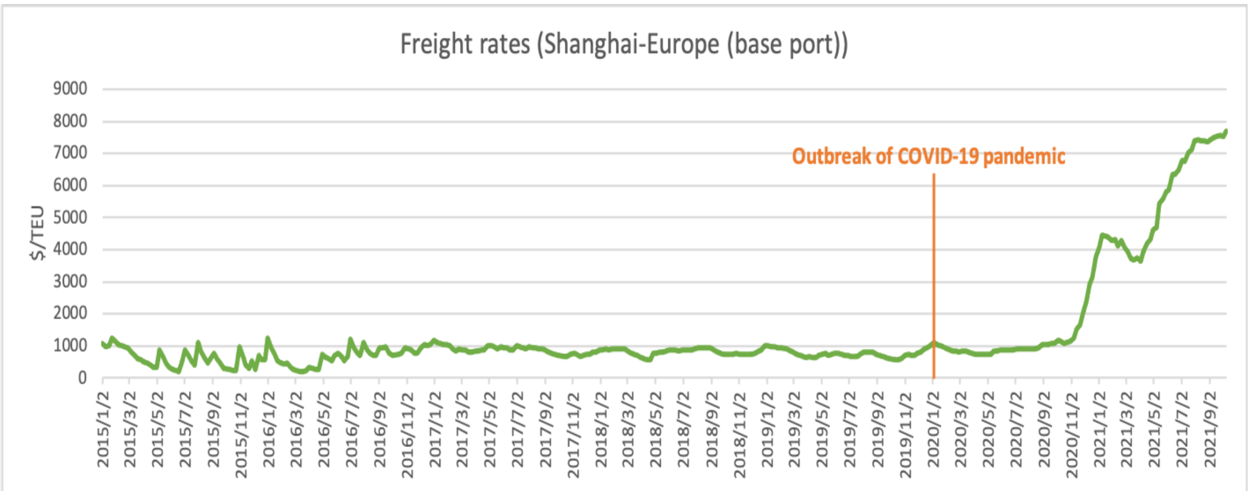

Figure 1. Shanghai Containerized Freight Index for Shanghai-Europe trade route (base port) $/TEU, from January 2, 2015 to October 8, 2021 (weekly data)

Data source: Shipping Intelligence Network Timeseries and United Nations Conference on Trade and Development (UNCTAD)

This research focuses on the shipping lane from Asia to Europe since it is one of the most important shipping routes in the world. According to Neves et al. (2019), "Asia and Europe are now leading trade partners, with $1.5 trillion of annual merchandise trade, overtaking each continent's trade with the United States". There are three shipping routes between Asia and Europe: the Suez route, the Cape route, and the North Sea route. Although reasons such as low fuel prices and ice receding make shipping companies commercially possible to choose the Cape route and the North Sea route, the Suez route is still the main commercial artery between Asia and Europe (Notteboom & Rodrigue, 2011). Due to the great impact of China's export trade on the container shipping market, as well as the shock of Suez Canal obstruction, the impact of the pandemic on the freight rates of this route can be representative of the shipping industry.

1.2 Problem Statement

Freight rates play an important role in the shipping industry since they serve as a mechanism for regulating supply and demand. The level of freight rates not only affect the cost of terms of trade, but also directly reflect the revenue of shipping companies (Luo et al., 2009; Stopford, 2009). Demand for shipping services is volatile and unpredictable, and more vulnerable to exogenous shocks (Stopford, 2009; UNCTAD, 2021b). That is why shortages of container shipping capacity have caused container shipping freight rates to soar during the COVID-19 pandemic and the Suez Canal blockage.

Such disruptive global events will not only cause short-term fluctuations in freight rates, but also disrupt global supply chains (Lam et al., 2021; McKinsey, 2022). It is the competitive advantage of shipping companies to grasp these market uncertainties brought about by exogenous shocks and related macroeconomic markets during that period and make more accurate forecasts on freight rates. In addition to being able to understand its potential risks and profitability at a specific time to help shipping companies make the right decisions at the right time, it is also essential to the long-term strategic and operational planning of shipping companies (Nielsen et al., 2014; Schramm & Munim; 2021).

At present, the studies on the modelling and forecasting of freight rates in the container shipping market are rare, and most studies focus on exploring the impact of long-term fluctuations on freight rates. This research not only focuses on short-term exogenous events, but also aims at freight rates in the container shipping market. Michail & Melas (2020) is the first to discuss the impact of a short-term collapse of the shipping cycle on freight rates in the dry bulk, clean and dirty tanker markets. This research further discusses the impact of the COVID-19 pandemic on the container shipping market. It fills in the gap in the literature by exploring the correlation between container shipping freight rates and the COVID-19 pandemic.

1.3 Purpose and Research questions

The outbreak of the COVID-19 pandemic has brought unpredictable effects to the container shipping market, which affects the fluctuation of container shipping freight rates. The purpose of this study is to investigate how container shipping freight rates on one of the most important shipping routes in the world, the Asia-Europe trade lane, respond to the COVID-19 pandemic, as well as the impact of the macroeconomic environment on freight rates, in order to understand the research subject from a more comprehensive perspective. Freight rates directly affect the revenues of shipping companies, and when affected by exogenous events, the fluctuation of freight rates can be more challenging to predict. If shipping companies know the relationship between the COVID-19 pandemic and container shipping freight rates, with incorporating the macroeconomic environment into the analysis, they can be better prepared for similar situations in the future.

The research questions of this study are:

1. How has the COVID-19 pandemic affected container shipping freight rates for the Asia-Europe trade route?

2. How have macroeconomic variables, especially oil prices and stock market prices, affected container shipping freight rates both during and before the pandemic?

1.4 Delimitations

This research is limited to and focuses on the container segment of the shipping industry, as well as the trade lane from Asia to Europe. The time period of the data is limited and the research cannot cover the latest data due to the availability of the freight rates data. In addition to the coronavirus variable, other variables included in our model are limited to macroeconomic variables, which particularly affect the demand side of the shipping market and can present short-term effects. The reason for limiting the scope of research to container shipping and the Asia-Europe trade lane is not only that they are the important segment and the main route in the shipping industry, but also that analysing the homogenous sector can ensure that the market behaves in a common manner.

1.5 Outline

In the introduction section, the background, problem statement, purpose and research questions, as well as some research delimitations, are stated to provide an overview of this research. The literature review includes two parts: container shipping market and container shipping freight rates, which provide a theoretical framework for key concepts of this research. In the methodology section, a brief introduction to the methodology used in this research, as well as the general version of the selected model (GARCH), its requirements and its strengths and weaknesses are presented. The following section discusses the dataset and the model for this research, as well as our assumptions about the model. In the empirical analysis and results section, our models' the empirical results and diagnostic tests are discussed, and the research questions are analysed. In the discussion section, more interpretations of the results of the analysis as well as further comparisons of the results before and during the COVID-19 pandemic are provided. Other events during the pandemic that also affect freight rates, such as the Suez Canal obstruction, and recent major events beyond the data period of this research, such as the war between Russia and Ukraine and Shanghai lockdown in 2022, are also explained in the discussion section, in order to have a better understanding of the freight rates changes in different periods. Finally, the conclusions and the contributions of this research are drawn.

2. Literature review

2.1 Container shipping market

2.1.1 Container shipping

Maritime transport facilitates global trade. There are three types of sea transportation: industrial, tramp, and liner shipping (Lawrence, 1972), but they are not mutually exclusive (Christiansen et al., 2004). The most commonly used mode is liner shipping. On the other hand, sea transport was also transformed by the expansion of international trade since the 1960s. The first container shipping was navigated by Malcom McLean for competing with other transporters in 1956, which became one of the most important milestones. Since then, the growth of global trade has increased the demand for container shipping (Lau et al., 2013). Containerized cargo has been the most dynamic cargo group and played about 60% of the value of goods transported by sea (Stopford, 2009).

Maritime containers are accepted widely due to the improved service levels. Port handling costs are reduced by the unitization of cargo, since the efficiency of cargo handling in port is improved (Ducruet & Itoh, 2021). In the early time of containerization, containers were mounted on wagons, which is inefficient due to the weight and space of wagons. Then, there were cranes on the ships to handle the containers between ships and yards. Finally, after certain technological progress, modern full-container ships without cranes on board were launched (Morel & Ducruet, 2015). Cranes were placed on berths to carry containers between ships and yards, while trucks and trailers transport containers into the yards (ibid). This helps to reduce the handling time on both sea and land sides. The temporal gaps between trade partners can be removed by containerization. For example, the duration of a round-trip between East Asia and North America decreased from 80 days in 1956 (early period of containerization) to 30 days in 1968 (full-container ship) (ibid).

In the 1990s, larger and fuel-economic vessels appeared on the market, which led to a substantial cost reduction (Notteboom, 2004). “Samsung demonstrated that a vessel of 12000 TEU on the Europe-Far East route would generate a 11 per cent cost saving per container slot compared to an 8000 TEU vessel and even 23 per cent compared to a 4000 TEU unit” (ibid). While it is difficult for carriers to gain full benefit from the economies of scale due to the poorer slot utilisation (Lim, 1998). Many shipping lines are not able to realise a continuous high utilisation of capacity on their bigger vessels.

The high value-added items such as consumption and intermediate goods are handled by containers, compared with dry bulk which transports raw materials. The demand for container shipping seems more volatile and the freight rate of container transport should be more volatile as well (Ducruet & Itoh, 2021). Alphaliner (2018) believed that the global container market is dominated by competitive oligopoly, which causes container shipping freight rates to fluctuate over a wide range. However, governments around the world, especially in the West, have regulated agreements that prohibit container shipping companies from setting fixed prices to avoid consumers being charged very high prices (Merk et al, 2018). This has led container shipping companies to establish alliances for mutual benefit. Furthermore, they have contributed to an increase in market power (ibid). This has stabilised container shipping freight rates to a certain extent, making container shipping less competitive than the bulk market (Rau & Spinler, 2016; Merk et al., 2018).

2.1.2 Global container shipping market

Worldwide container port throughput increased from 266 million TEU in 2002 (OSC, 2003) to 827 million TEU in 2021 (Statista, 2021). The rise of world containerisation is the result of the interplay of macroeconomic, microeconomic and policy-oriented factors (Notteboom, 2004). Before the mid-1990s, most containers were handled in developed countries, while Chinese ports increased their container handling volume after 1995. Nowadays, the total Chinese share including Hong Kong is more than 30%, while European ports witnessed a decrease from 30% in 1975 to 12% in 2015 (Ducruet & Itoh, 2021). The share of Asia in worldwide container port throughput rose from 25% in 1980 to about 46% in 2004 (Notteboom, 2004). Ducruet & Itoh (2021) also stated "The distribution of containers and economic activities had been tightly connected until 1999". While in the 2000s, more container traffic moved to Asia, more than 25% of the containers concentrated in the region. In 2006, the major container shipments were concentrated in East Asia, Asia and Europe, and Trans-Pacific (Ducruet et al, 2020). This can be explained by the regional integration of East Asia and the major link between Asia and Europe. Trans-Pacific trade is also a crucial part of global trade, but a large proportion of empty containers move from North America to Asia, which is caused by the imbalance of trade between the two regions (ibid). Containerization increased the speed of economic growth in emerging economies. On the other hand, it also expanded the imbalance of cargo movements on routes and regions throughout the world (Ducruet & Itoh, 2021).

Shipping lines merge and acquire under the horizontal integration strategies. Maritime containers are transported by several large companies, often through alliances. As it is described in section 2.1.1, the alliance is the way that container shipping lines consolidate market power under governments' antitrust regulation. Such alliances are increasingly concentrated and have accelerated after the 2008 financial crisis (Ducruet & Itoh, 2021). When the economy is in recession, shipping lines usually deploy the slow steaming strategy which is gaining economies of scale, saving fuel and cost by low travel speed and larger vessel size. The shipping industry is changing. Alternative shipping routes such as China Maritime Silk Road may decrease the shipping cost (Wang et al., 2018). Other new routes including a new Nicaragua Canal replacing Panama Canal and a railway land bridge through Israel replacing Suez Canal are also able to reduce the shipping cost in the future (Ducruet & Itoh, 2021).

The demand of the global maritime shipping market is affected by regular, short-term and medium-term fluctuations (Grzelakowski, 2019). It is common that there is a mismatch between the supply and demand in the container shipping market, which leads to an imbalanced market (ibid). Furthermore, the imbalance between commodity sequences in the main container routes deepen the imbalance of the market (UNCTAD, 2018; WSC, 2018).

2.1.3 Container shipping between Asia and Europe

According to Ohmae (1985), the world economy is facilitated by North America, Europe and Asia. They produce 80% of exports and 83% of imports in international trade. As it mentioned in the global container shipping market, the container shipping is concentrated in the Northern hemisphere and traffic between North America, Europe and Asia. Since 1980, Asia has become the industrial centre of the world and the consumer market is booming (Leinbach & Capineri, 2007). Maritime container traffic linking Asia with Europe and North America has become the principal axis of the global container market (Verny & Grigentin, 2009).

The container shipping market between Asia and Europe is the largest one in the world, with volume as high as 25 million Twenty-Foot Equivalent Unit (TEU) in 2019 (Liu et al., 2021). According to UNCTAD (2021b), the volume of container shipping between Asia and Europe is 26.3 million TEU in 2021, and is one of the busiest shipping routes in the world. As early as

2005, certain reports predicted that the total volume of maritime container traffic between Asia and Europe would increase by more than 600% by 2030. This number corresponds to a mean annual growth rate of 24% over 25 years (Großmann et al., 2006).

To meet the continuous growth in containerized trade, shipping lines increase the size of container ships, which on the other hand reduce the westbound maritime container freight rate (Verny & Grigentin, 2009). One of the reasons for the increase in container freight rates is due to unbalanced traffic flows between Asia and Europe. The majority of containers are transported from Asia factories to Europe the consumer market: about two TEUs leave Asia for every TEU leaving Europe (OECD, 2006). The price of sending a container to Europe includes the cost of returning an empty container to Asia (Shy, 2008). In 2007, the cost of transporting a container between two fixed ports was on average three times higher for routes from Asia to Europe than the inverse (Verny, 2007).

There are two route choices when shipping lines transport cargo between Europe and Asia, which are the Cape route and Suez Canal route. According to Notteboom (2012), the dominant one has become the Suze canal route due to its upgrading in the last 50 years. Verny & Grigentin (2009) also stated that shipping through the Suez Canal is still by far the least expensive and time-saving option in the Asia-Europe transport network. The Suez Canal plays an important role in container shipping especially in the trade routes between Asia and Europe. Notably, nearly 93% of these container flows are related to the Asia-Europe trade routes. While in 2008, Drewry predicted that the Suez Canal would soon reach its capacity limit. The Suez Canal expansion was completed in 2015. In March, 2021, Suez Canal was blocked due to the grounding of Ever Given which led to discussions not only about the larger size of vessels but also about alternative routes - the Northern Sea Route (NSR).

In fact, the feasibility of NSR has been already discussed by scholars before the accident. The Northern Sea Route (NSR) is a maritime route between the Atlantic and Pacific Oceans along the Russian coast of Siberia and the Far East. The future Arctic glaciers recession will make it possible to put the NSR route into commercial use. NSR saves 40% of shipping distance from Asiato Europe compared to the Suez Canal route (Notteboom, 2012). Schøyen & Bråthen (2011) stated that NSR could save fuel costs, reduce congestion in the canal. They also believe that the route is more suitable for bulks due to the seasonality.

2.2 Container shipping freight rates

2.2.1 The importance of freight rate mechanisms

The shipping market is greatly affected by the supply and demand of the market. Freight rates are the price performance of the changes in the supply and demand structure of the shipping industry, which are mainly determined by the supply of world fleet capacity and the demand for shipping services derived from global seaborne trade volumes (Stopford, 2009; Nielsen et al., 2014). Freight rates also control the cash flow paid by shippers to shipowners for transporting cargoes, which can be considered as the main source of income for shipping companies (Stopford, 2009).

Since the demand for shipping services is changed by the demand and pattern of global trade, and the demand is volatile, fast-changing and unpredictable, on the other hand, the supply is often large and slow-moving, it is very rare to achieve stable returns. Furthermore, when the market is closely balanced, the freight rate mechanism will magnify small imbalances on the margin (Stopford, 2009). In the face of market uncertainty, freight rates will be affected by dynamic uncertainties, which in turn will affect shipping revenue. Therefore, the ability to predict freight rate trends is a competitive advantage for shipping companies when dealing with market ups and downs (Bendall & Stent, 2010; Nielsen et al., 2014).

2.2.2 Factors affecting freight rates

Shipping freight rates are affected by many factors. Stopford (2009) listed five factors that mainly affect the shipping demand, including world economy, seaborne commodity trades, average haul, random shocks and transport costs, and five factors that mainly affect the shipping supply, including world fleet, fleet productivity, shipbuilding deliveries, scrapping and freight revenues. As mentioned in section 2.2.1, the demand for shipping services is easily affected by many unpredictable factors, and the supply in the shipping market often changes with its demand. Therefore, under a certain supply condition, the change of the freight rate reflects the change of the shipping demand (Fusillo, 2004; Michail, 2020). For the relevant variables affecting demand in the shipping market, in the long run, the freight rate may be affected by the economic condition of the importing and exporting countries, as well as the national policies of supply and demand of major raw materials. In the short term, if the cargo flow is affected by off-peak seasons, the freight rate may repeat periodically and cause similar price fluctuations, while if it is affected by random shocks, such as the financial crisis and the COVID-19 pandemic, the fluctuation of the freight rate will be more difficult to predict (Yin & Shi, 2018; Notteboom et al., 2021).

In the research of shipping freight rates, the analysis of the relevant markets which will affect the shipping industry cannot be ignored. The shipping market is dependent on international trade. Since China is the world's largest trading country, which is also the number one connected country in the world, China's impact on the shipping industry should not be underestimated (UNCTAD, 2019; Gu et al., 2020). Gu et al. (2020) showed that China and its representative freight rate are closely linked with the global shipping market. Chen et al. (2021b) also indicated that the relationship between freight rates and the trade volume as well as GDP growth of China is significant.

Macroeconomic variables are also important factors affecting the fluctuation of freight rates (Lim et al., 2019; Michail, 2020). Oil prices are directly reflected in the transport cost of shipping companies, and any sudden changes in the crude oil market will affect the shipping market (Shi et al., 2013; Gavriilidis et al., 2018; Gu et al., 2020). On the other hand, due to the long-term contracts for fuel and lubricants, oil prices may not fluctuate significantly in the short term, so that freight rates will not be affected accordingly (Michail & Melas, 2020). Although most of the research which explores the impact of oil prices on freight rates focuses on the dry bulk and tanker markets (Gavriilidis et al., 2018; Michail & Melas, 2020), there has still been some research finding that oil prices have a significant impact on the performance of the container shipping market (Grammenos & Arkoulis, 2002; Drobetz et al., 2010).

The stock market can reflect market sentiment for the macroeconomic environment. It can be used to represent industrial and consumer activity as it can quickly capture changes in shipping company profits and future potential of importing and exporting countries (Gu et al., 2020; Michail & Melas, 2020; Michail & Melas, 2021). Papapostolou et al. (2016) showed that market sentiment is a significant factor for the returns on the container shipping market. Erdogan et al. (2013) also showed that there are consistent changes in the relationship between the stock and shipping markets, and that the relationship has a higher degree of tightness during cyclical depressions.

2.2.3 The impact of exogenous shocks on freight rates

Although exogenous events can have a strong impact on a shipping company's cash flow, previous research has not focused extensively on event studies in the shipping industry (Michail & Melas, 2020). Exogenous events which usually affect the demand of shipping services will change the shipping business cycle, and then the supply of shipping will adjust the changes in demand represented through endogenous breaks in the shipping companies (Abouarghoub et al., 2012). In the short term, exogenous shocks contribute to the uncertainty and volatility of the shipping market, making it more difficult to predict container freight rate fluctuations (Lam et al., 2021).

In the shipping industry, relevant event research mainly comes from the discussion of endogenous events, and the most common research focuses on the impact of shipping company mergers and acquisitions on company stocks (Panayides & Gong, 2002; Alexandrou et al., 2014). Thanopoulou & Strandenes (2017) categorised disruptive events and discussed their risks to the shipping market extensively, but the study did not specifically mention the impact of these exogenous shocks on shipping freight rates. Only some research pointed out that exogenous shocks such as the global financial crisis or the COVID-19 pandemic affect freight rate volatilities (Tsouknidis, 2016; Michail & Melas, 2020). Although exogenous events will affect the shipping industry in the short or the long term, such exogenous shocks will first cause short-term fluctuations in freight rates (Michail & Melas, 2020). However, most studies on shipping freight rates are based on analysis and forecasting for longer periods. This may ignore the intensive impact of short-term uncertainty (Thanopoulou & Strandenes, 2017).

2.2.4 Modelling and forecasting of freight rates in the container shipping market

Freight rates behave very differently in different shipping freight markets (Li et al., 2018). Although freight rates adjust the demand and supply in any shipping segments, comparing bulk shipping with container shipping, bulk shipping has the characteristics of a perfectly competitive market, while container shipping is less competitive due to the cooperative agreements, and its demand is infinitely divisible (Rau & Spinler, 2016). Many research has been devoted to the dry bulk and tanker markets in the past (Cullinane et al., 1999; Adland & Cullinane; 2006; Chen et al., 2012; Abouarghoub et al., 2018), but relatively few studies have discussed the modelling and forecasting freight rates in the container shipping market, and related articles have only been published in recent years (Luo et al., 2009; Nielsen et al., 2014;

Jeon et al., 2019; Chen et al., 2021a). One of the important reasons is that the container shipping freight rates do not have a reasonable length and consistent price, which makes forecasting more difficult (Nielsen et al., 2014).

The mainstream methods used in forecasting container shipping freight rates include Autoregressive integrated moving average (ARIMA), Vector Autoregression (VAR), Vector error correction (VEC), and their variants ARIMAX, VECX which adds exogenous variables (Li et al., 2018; Munim & Schramm, 2021). In addition, the General autoregressive conditional heteroscedasticity (GARCH) model, the System-dynamics model, and the Grey wave forecasting model have also been used in recent articles. The GARCH model is able to capture volatility clusters in shipping freight returns, the System-dynamics model can generate dynamic patterns in order to capture interdependencies among shipping freight rates, and the Grey wave forecasting model achieves good results in predicting highly volatile time series (Jeon et al., 2019; Li et al., 2018; Michail & Melas, 2020; Chen et al., 2021a).

Many pioneers in forecasting container shipping freight rates used the ARIMA method, among which Munim & Schramm (2017) provided better weekly short-term forecasts for the Shanghai containerized freight index (SCFI) and the China containerized freight index (CCFI) through this method, and also found that this method is appropriate for out-sample forecast of container shipping freight rates. In the subsequent study (Munim & Schramm, 2021), the conclusion has been made that the effect is better than using VAR, and using ARIMAX can have better prediction effects than using ARIMA. However, the weakness of ARIMA may be its poor performance when applied to volatile time series data (Petrică et al., 2016).

Jeon et al. (2019) analysed the cycle of CCFI by implementing the System-dynamics model which reflects the factors of both supply and demand. It can achieve multivariate system equilibrium compared with traditional univariate methods for a more comprehensive analysis. Chen et al. (2021a) combined the empirical mode decomposition (EMD) and the Grey wave methods to predict the trend term with GM and the short cycle through Grey wave, which can predict the fluctuations of freight rates in different periods in order to improve the accuracy. In addition, there have been several articles that contribute to the forecasting of container shipping freight rates through other methods, such as Luo et al. (2009) using a supply and demand model to construct a function of fleet capacity to predict freight rates, and Nielsen et al. (2014)

predicting freight rates by using econometric models to study the relationship between market rates and individual liner rates.

3. Methodology

The section of methodology consists of several parts. First, the research philosophy and method are stated. The reason why the quantitative method is chosen is also given. Then the research process is presented step by step, starting from literature review, data collection to modelling.

The aim of the research is to find whether there is a correlation between different variables. These variables are quantified, setting the tone for the research philosophy - positivism. Generally, positivism research is based on facts, testing a conclusion or hypothesis by statistical analysis. The data collection and interpretation are in an objective way. Besides, positivism follows a well-defined structure during research and discussions (Collis & Hussey, 2014). There is low probability of error since positivism research follows specific laws and rules by using objective mathematical and scientific tools (ibid). While at the same time, specific laws and rules lead to the inflexibility of positivism study which needed to be considered when conducting positivism research.

Based on the positivism research philosophy, the quantitative method is used to investigate if there is correlation between container shipping freight rates and factors including COVID-19 cases, oil prices, and stock market prices. These factors were not arbitrarily decided but confirmed based on literature review.

The first step of this research was literature review, and one of the main goals is to find out which variables, especially macroeconomic variables, are related to the dependent variable - container shipping freight rates, and the impacts they bring. Data collection was then performed according to the variables explored in the literature review, including the Shanghai Containerized Freight Index (SCFI), the number of confirmed COVID-19 cases in Asia and Europe, the Brent Oil Price, and the stock market prices (Shanghai Composite Index & Euronext 100). All the data is secondary data and collected from reliable data providers.

Data collection and processing were completed before the modelling. As this study chose to use weekly SCFI for the analysis, in addition to the weekly data on the number of confirmed new coronavirus cases, the average of the Brent Oil Price over the week and the medians of the Shanghai Composite Index and the Euronext 100 Index over the week were calculated to present weekly data. The characteristics of the GARCH model were introduced, and its strengths and weaknesses compared with other methods were further discussed, to illustrate the reasons for adopting the GARCH method in this research. The GARCH model is an extension of the ARCH model (Engle, 1982) and was developed by Bollerslev (1986), which accurately models change in the volatility of time series variables (Engle, 2001; Lanne & Saikkonen, 2005; Li et al., 2018).

3.1 General version of GARCH

The GARCH (p,q) model is a generalised Autoregressive Conditional Heteroscedasticity model. p indicates how many autoregressive lags or ARCH terms appear in the equation, and q indicates how many moving average lags or GARCH terms are specified (Hamilton, 1994; Engle, 2001; Brockwell & Davis, 2016). The GARCH model takes into account the different effects of negative and positive shocks on volatility, which is the limitation of the ARCH model. This assumption is more in line with the characteristics of financial assets in reality (Ruslan & Mokhtar, 2021). Following is the form of the variance in a general GARCH model:

$$\alpha_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \alpha_{t-j}^2$$

where ε_t is the residual, α_t^2 is the conditional variance, and α_0, α_i, β_j are parameters to be measured. For the model to be valid, some requirements must be met: $\alpha_0 > 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$, and $\sum(\alpha_i + \beta_j)$ should be close to 1. For financial time series data, α_i represents the volatility of sensitivity to market shocks, and β_j represents the persistence of market shocks (Ruslan & Mokhtar, 2021).

GARCH (1,1) is the most widely used GARCH model, which has been shown to perform well in previous studies (Andersen & Bollerslev, 1998; Brooks & Burke, 2003; Hansen & Lunde, 2005). The variance equation for GARCH (1,1) is:

$$\alpha_n^2 = \gamma V_L + \alpha \varepsilon_{n-1}^2 + \beta \alpha_{n-1}^2$$

which is calculated from the long-run average variance, V_L, and the lag terms of ε_{n-1} and α_{n-1}. ε_{n-1}^2 represents the most recent squared residual, which captures the new information about volatility from the previous period; α_{n-1}^2 represents the most recent variance. It means the variance at time t is not only affected by the previous volatility news, but also by the previous conditional variance (Engle, 2001; Ruslan & Mokhtar, 2021). In order to meet the condition that the variance is non-negative, γV_L, α and β should be non-negative. $\alpha + \beta$ should also be close to 1.

3.2 Stationarity

Stationarity is the foundation of time series analysis. By strict definition, a stationary time series exhibits similar statistical behaviour in time, which is also known as a constant probability distribution in time, but it is almost impossible to satisfy in reality. In practice, the definition of weak stationarity is generally adopted, which includes two conditions: the expected value of the time series does not depend on time, and the variance of the time series does not change with time. Misleading conclusions may be drawn if using non-stationary data for modelling (Hamilton, 1994; Montgomery et al., 2015). In statistical analysis, there are various unit root tests to test the stationarity of the series, such as the most common Augmented Dickey–Fuller (ADF) test (Dickey & Fuller, 1979), others such as Phillips and Perron (PP) test (Phillips & Perron, 1988) and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test (Kwiatkowski et al., 1992).

3.3 Volatility

Volatility is the conditional variance of the dependent variable in the time series model. It is generally assumed that the conditional variance of a time series does not change over time, but this is rarely the case in reality. Constant volatility is called homoscedastic, while non-constant volatility is called heteroscedastic. The heteroscedasticity problem refers to the fact that the error variance is related to the squared error term of the previous period. If it is heteroscedastic, the volatility value can be calculated by using ARCH/GARCH methods (Engle, 2001; Brockwell & Davis, 2016). Furthermore, the ARCH–LM test can test whether the variance is constant or changing over time, which can also be said to test whether there is an ARCH effect in the residuals of the time series (Engle, 1982; Baum, 2014).

3.4 Strengthens and Weaknesses of GARCH

The dynamics of the conditional variance are especially important in financial models. Financial time series data usually has the feature of volatility clustering (Engle, 2001; Lanne & Saikkonen, 2005; Brockwell & Davis, 2016). Volatility has a strong continuity, that is, large fluctuations are accompanied by large fluctuations, and small fluctuations are followed by small fluctuations. This can lead to difficulties for modelling as the model needs to adapt quickly to structural changes in volatility (Tsay, 2005). In addition, most of the distributions of this kind of data have thick tails, which means there are more extreme values. These features can be captured using ARCH/GARCH models, which cannot be realised in traditional time series models, such as VAR, VEC, and ARMA models (Engle, 2001; Brockwell & Davis, 2016; Li et al., 2018).

However, one major drawback of the GARCH (1,1) model is exploring the non-linear structural changes in dynamic volatility processes. The structural changes are also possible to affect the volatility of shipping freight rates. Some articles have applied copula technique or other transition functions to address the potential non-linear interdependencies between shipping freight rates (Liu et al., 2012; Li et al., 2018). Furthermore, there have also been some recent studies showing that non-traditional methods such as the System-dynamics model, the Grey wave forecasting model, and other neural network forecasting models can deal with more complex and non-linear features in time series data (Jeon et al., 2019; Chen et al., 2021a).

4. Dataset and Model

4.1 Dataset

4.1.1 Variable descriptions and data collection

This research uses the quantitative data from January 2, 2015 to October 8, 2021 to study the reactions of freight rates on the COVID-19 pandemic for container shipping for the Asia-Europe trade lane. Since the World Health Organisation (WHO) started to collect the data of the number of confirmed COVID-19 cases and deaths from December 31, 2019, the coronavirus variable is only available from that date, while the data range is limited by the availability of the freight rates data. The data range is only up to October 8, 2021 due to the accessibility of freight rates data, and the reason why the data for this research was collected from 2015 is because it could avoid covering the severe shocks to global markets caused by the financial crisis in 2008 and the Donbass strategic offensive in 2014. The selection of the data period starts from 2015, so as to avoid the problem that too long a time frame tends to create more uncertainty and too short a time frame constrains research. Under such data period selection, the market is relatively representative.

Since container shipping freight rates are cyclical in nature and can fluctuate significantly within a week (Munim & Schramm, 2017), weekly container shipping freight rates are used to carry out the analysis. The Shanghai Containerized Freight Index (SCFI) fluctuates up and down according to the spot rates of the Shanghai export container transport market. It is the most commonly used indicator for shipping freight rates from China, which is also an indicator of the health of global trade since it regulates the supply and demand of the shipping market. The SCFI is based on 20-foot containers. This research uses the SCFI on the Shanghai to Europe trade route, and for Europe, it is based on the discharge ports of Rotterdam, Hamburg, Antwerp, Felixstowe, and Le Havre (DSV, n.d.). The SCFI data was obtained from Shipping Intelligence Network Timeseries and United Nations Conference on Trade and Development (UNCTAD).

The number of confirmed new coronavirus cases in Asia and Europe in a week are collected for correlation analysis between the COVID-19 pandemic and container shipping freight rates. As one of the main independent variables in the model, confirmed cases quantifies the COVID-19 pandemic level intuitively. The weekly number of new cases provided by WHO is calculated by subtracting the previous cumulative total from the current week number (WHO, n.d.). Asia and Europe are the main subjects of the study. Weekly data on confirmed new coronavirus cases in Asia and Europe were obtained from WHO.

In addition to the impact of the coronavirus outbreak on freight rates, the Brent Oil Price as well as the stock market prices (Shanghai Composite Index & Euronext 100) are used to depict the macroeconomic market outlook. Brent crude usually refers to the price of the ICE Brent Crude Oil futures contract or the contract itself (Soni, 2020). Brent oil is produced in the Brent region of the North Atlantic North Sea, so traders are mostly from neighbouring European countries (Inkpen & Moffett, 2011). Brent crude is an international crude oil valuation system. Meanwhile, it is also the world's leading and most widely used and referenced oil price benchmark. Bernt dictates the value of 2/3 of the world’s crude oil supplies (Hecht, 2014). Another main crude oil is West Texas Intermediate (WTI), which is more commonly used in North America. Due to the wider use of Brent crude and the fact that this study focuses on the Asia-Europe route, Brent Oil Price is collected to be the oil price variable in the model. The data was obtained from Federal Reserve Economic Data (FRED) which is an online database covering hundreds of thousands of economic time-series data from a variety of public and private sources. Besides, FRED also illustrates the data by powerful tools to make the data easier to understand (FRED, n.d.). The database offers the data of Crude oil prices: Brent-Europe on a daily basis. The authors averaged for each 7-day data to represent weekly data. Since oil prices move slowly, which means there may not be much change in a week, and extreme values are less likely to occur, using the average can better reflect the information contained in the data for a week.

The Shanghai Stock Exchange (SSE) is the largest stock exchange in Asia. The Shanghai Composite Index, also known as SSE Composite is the most widely used index to reflect the market performance of SSE, which is a stock market composite index consisting of all A-shares and B-shares traded on the SSE (Chen, 2021). The Euronext is the largest stock exchange in Europe, which creates many popular European benchmark indices. The Euronext 100 is a stock market index that includes the largest and most liquid stocks traded on the Euronext (Scott, 2021). This research uses the Shanghai Composite Index to represent the impact of the Asian macroeconomic market and the Euronext 100 to capture the European macroeconomic impact. Both of the stock market data were obtained from Yahoo Finance. Since the data on stock market prices are daily data, the authors calculated the median over a week. The choice for the median is because the stock price may fluctuate significantly over a week, and using the median can avoid extreme values. Table 1 shows more details on variable descriptions.

Table 1. Variable descriptions[1]

Variable	Description	Source	Unit of measurement
SCFI	Shanghai Containerized Freight Index	Shipping Intelligence Network Timeseries / UNCTAD	Index
Coronavirus_Asia	The number of confirmed new cases in a week - Asia	WHO	Number of people
Coronavirus_Europe	The number of confirmed new cases in a week - Europe	WHO	Number of people
Oil Price	Weekly average of Brent Oil Price (Brent-Europe)	FRED	Dollars per barrel
Stock_Asia	Weekly median of Shanghai Composite Index	Yahoo Finance	Index
Stock_Europe	Weekly median of Euronext 100	Yahoo Finance	Index

4.1.2 Basic statistics of the variables

The number of confirmed COVID-19 cases (new confirmed cases per week) is the main focus of this research on freight rates. From Figure 2, in Asia and Europe, the outbreak of the pandemic has gone through several stages. Although the number of confirmed cases in Asia climbed faster in the first wave of the pandemic, strict control measures were implemented in Asian countries. Therefore, the pandemic was brought under control after September 2020. In April 2021, the pandemic in Asia broke out again. This may be caused by the invasion of a variant virus. However, after a month, the number of confirmed cases dropped rapidly and has maintained a downward trend. On the other hand, in European countries, since the number of confirmed cases rose sharply in October 2020, despite several fluctuations, the pandemic has not been brought under control. Although in April 2021, the situation seemed to have begun to improve, it has shown an upward trend after July 2021.

[1] For more information about data access and data processing, please contact the authors by email at gusyucch@student.gu.se, or gusshizh@student.gu.se.

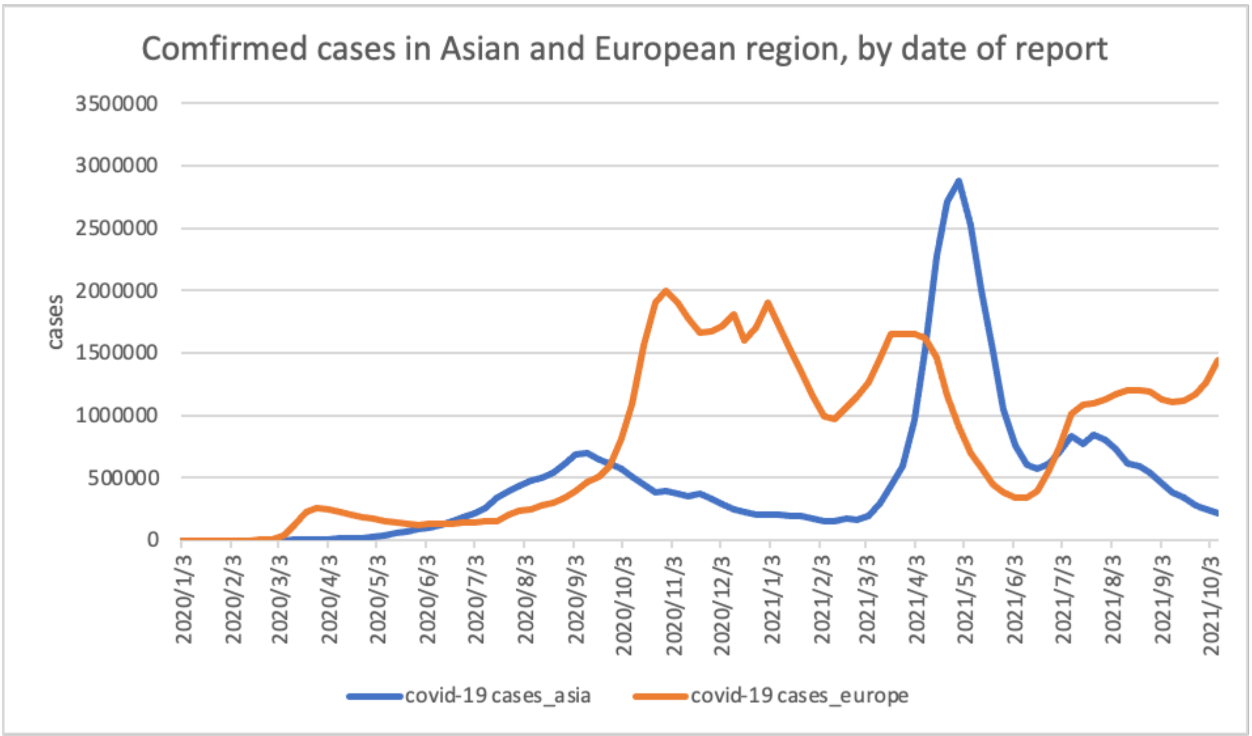

Figure 2. The number of confirmed COVID-19 cases (new confirmed cases per week) in Asian and European region, from January 3, 2020 to October 8, 2021

Data source: World Health Organisation (WHO)

Basic Statistics of the variables are reported in Table 2. Observations are 344 (weeks) in total, and observations after the outbreak of COVID-19 pandemic (January 3, 2020) are 91 (weeks). Before the COVID-19 pandemic, Table 2 shows the mean SCFI is 755.43 $/TEU; however, during the COVID-19 pandemic, the mean SCFI becomes 3165.39 $/TEU. The range and the standard deviation of the SCFI also become very large after the outbreak of the COVID-19 pandemic. It can also be seen from Figure 1 in the introduction section that, overall, freight rates have shown a sharp upward trend during this time period. The maximum value reaches 7714 $/TEU, which is more than ten times the minimum value. The range and the standard deviation of the number of confirmed new coronavirus cases in Asia and Europe in a week are also large. It is evident from Figure 2 that new confirmed cases per week for both Asia and Europe have changed dramatically over time. Although the maximum number of confirmed new cases in Europe in a week is not as high as in Asia, the average number during this period is about 1.5 times that of Asia. For variables such as the Brent Oil Price, the Shanghai Composite Index, and the Euronext 100, their values do not differ significantly before and during the COVID-19 pandemic, except that the standard deviation of the Shanghai Composite Index before the pandemic is much larger than the standard deviation of the Shanghai

Composite Index during the pandemic. After the outbreak of the COVID-19 pandemic, the mean Brent Oil Price is 53.28 dollars per barrel, and for stock market prices, the mean Shanghai Composite Index is 3307.24, and the mean Euronext 100 is 1099.69. Whether before or during the COVID-19 pandemic, the medians for the variables of oil prices and stock market prices are very close to their averages.

Table 2. Basic Statistics of the variables

Variable		**mean**	**median**	**sd**	**se(mean)**	**min**	**max**	**N**
SCFI (Index)	before COVID-19	755.43	774	215.93	13.58	205	1256	253
	during COVID-19	3165.39	2091	2498.25	261.89	725	7714	91
Coronavirus_Asia (Number of people)	during COVID-19	478952.5	340495	581168.2	60922.98	0	2880197	91
Coronavirus_Europe (Number of people)	during COVID-19	807498.2	748781	627223.6	65750.9	0	1997275	91
Oil Price (Dollars of barrel)	before COVID-19	56.95	56.57	11.50	0.72	27.76	83.05	253
	during COVID-19	53.28	54.09	16.80	1.76	14.24	82.01	91
Stock_Asia (Index)	before COVID-19	3168.31	3113.35	415.37	26.11	2479.59	5117.56	253
	during COVID-19	3307.24	3390.28	265.97	27.88	2755.26	3685.76	91
Stock_Europe (Index)	before COVID-19	979.58	992.18	80.64	5.07	795.17	1154.05	253
	during COVID-19	1099.69	1110.15	143.74	15.07	764.65	1322.26	91

4.2 Model

Our model implements the GARCH method to examine the correlation between the COVID-19 pandemic and container shipping freight rates. The mean equation of the GARCH (1,1) model includes the dependent variable - *SCFI*, and the independent variables - the previous value of *SCFI*, *Coronavirus_Asia*, *Coronavirus_Europe*, *Oil Price*, *Stock_Asia* and

Stock_Europe. Some transformations of the variables will be made to meet the requirements of the GARCH method or to make the model results easier to interpret, which will be explained in more detail in the empirical analysis and results section.

4.2.1 Our expectations

It is difficult to predict the correlation between the COVID-19 cases and container shipping freight rates because there are too many factors needed to be considered. In our opinion, the expected correlation between them is positive or zero. The increased COVID-19 cases may lead to an increase in container shipping cost. For instance, the closure of ports due to the pandemic outbreak will put the shipping system under pressure, which will increase the uncertainty of shipping cost. Port operation will be negatively affected by the increased infection rates among port workers. The efficiency of port handling may decrease, leading to an increase in the overall cost. On the other hand, the number of cases may only be an additional factor which leads to a worse business environment. From this point of view, the number of confirmed cases would not have a significant impact on freight costs. However, after nearly a year of the pandemic, the economy has recovered, coupled with changes in consumers' consumption habits under the pandemic, which has led to a rapid rebound in container shipping demand from the slowdown. Therefore, it is difficult to assume the relationship between the COVID-19 cases and container shipping freight rates.

Brent crude is predicted to have a positive or zero correlation with container shipping freight rates. The increase of crude oil prices will lead to an increased fuel cost. As a result, the freight rate will increase. While long-term contracts for fuels and lubricants could keep the freight rate from being affected in the short term. In other words, oil prices may not be closely related to freight rates.

Stock market prices are considered to be a barometer of the macroeconomic market. In times of economic prosperity, companies make more profits, and industries have good prospects, which makes their stock prices rise. Therefore, the trend and changes of the stock market are determined by the level of economic development and economic prosperity of a country. Since the world economy generates most of the demand for shipping, driving global seaborne trade, our expectation is that these stock market indices should have a positive relationship with container shipping freight rates.

5. Empirical analysis and results

A stationarity test of the variables is required for time series models. After confirming that the requirement of the stationarity is fulfilled, the analysis of the GARCH model proceeds. The results of model diagnostic tests are also presented. Since the units of these variables are different and their ranges vary widely, the variables take log-transformation in the regressions to show the changes in percentage.

5.1 Stationarity check -Unit root tests

The GARCH method can only be applied to a dataset if it is stationary, meaning that the data does not have any trends or seasonal effects. In order to ensure that the dataset is appropriate for the GARCH method, the Augmented Dickey–Fuller test (ADF test) is implemented to test the stationarity of the dataset.

The dependent variable - SCFI may be nonstationary, since there would be seasonal effects in the container shipping freight rates. For example, during Christmas or Chinese New Year, the freight rates will be higher due to the high demand (Yin & Shi, 2018). From Table 3, the results for the ADF test show that the τ_s is -3.330, and the p-value is 0.0615. When using the 5% significance level, it is not significant (p-value = 0.0615 > 0.05); however, when using the 10% significance level, it shows statistical significance (p-value = 0.0615 < 0.1). It can be said that there may be a seasonal trend in the SCFI series, but in this selected time period, the seasonal effects do not bring much influence. For other independent variables - the number of confirmed COVID-19 cases in Asia and Europe, oil prices and stock market prices, except the series of coronavirus variables, all other macroeconomic series are non-stationary. Before regression analysis, they must be converted to stationary series, and taking first-difference is the most common way to eliminate the non-stationary series (Hamilton, 1994). The first-difference of the natural logarithm represents the growth rate. As shown in Table 3, after taking the first difference, the series of these macroeconomic variables are stationary.

Table 3. Stationarity check -the results for ADF test

Variable	ADF	
	τ_s (p-value)	**First Difference**
log(SCFI)	-3.330* (0.0615)	
log(Coronavirus_Asia)	-9.268*** (0.000)	
log(Coronavirus_Europe)	-6.673*** (0.000)	
log(Oil Price)	-1.905 (0.6521)	-13.272*** (0.000)
log(Stock_Asia)	-2.092 (0.5506)	-14.655*** (0.000)
log(Stock_Europe)	-2.413 (0.3725)	-15.043*** (0.000)

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% significance levels, respectively.

5.2 GARCH results

Table 4 shows the results for the SCFI using the GARCH (1,1) model. In equation (1) - (7), the results show that the SCFI strongly depends on its previous value, at more than 0.98. In equation (2), the SCFI is less affected by its two lags effect, and the effect is insignificant. Hence, only the previous SCFI value will be included in the following equations.

In equation (3), the coronavirus impacts for Asia and Europe are added to the model. These variables are assumed to have a positive relationship with freight rates, since they will lead to an increase of container shipping cost. The coronavirus impact for Asia is statistically significant, and it is positively correlated to the SCFI; however, the coronavirus impact for Europe is negatively correlated to the SCFI with an insignificant effect. This may be because the two variables are highly correlated, despite the different peak times of the pandemic in Asia and Europe as shown in Figure 2. Therefore, only the number of confirmed COVID-19 cases in Asia will be included in equation (4) - (7).

In equation (4), when considering the macroeconomic variables for oil prices and stock market prices, including the Brent Oil Price, the Shanghai Composite Index, and the Euronext 100, the number of confirmed new cases in Asia in a week still has a significant and positive association with the SCFI, at 0.0021. It implies that a 1% change in new confirmed cases per week in Asia would have an additional impact of 0.0021% on the SCFI. The growth rates of the macroeconomic variables are used in equation (4). However, the impacts of these macroeconomic variables are not significant.

In equation (5), (6) and (7), one of the macroeconomic variables is dropped from equation (4). Among these regressions, the impacts of the previous value of the SCFI and the number of confirmed new cases in Asia on the SCFI do not have a big difference. When only including the variables of stock market prices, the results show that the growth rate of the Euronext 100 has a positive relationship with the SCFI, which is also statistically significant. Although the growth rate of the Shanghai Composite Index is still negatively correlated with the SCFI, which is inconsistent with our assumption, it does not show a significant effect. In equation (6), the growth rate of the Brent Oil Price and the growth rate of the Shanghai Composite Index are included. They both have a positive relationship with the SCFI, but it is still insignificant. The growth rate of the Brent Oil Price and the growth rate of the Euronext 100 are then included in equation (7). The growth rate of the Brent Oil Price still shows insignificant effect. On the other hand, as the same results in equation (5), the growth rate of the Euronext 100 has a significant and positive association with the SCFI. It is also interesting to note that the growth rate of the Euronext 100 has the strongest relationship with the SCFI among these macroeconomic variables, at 0.2643. It can be interpreted that a 1% increase in the growth rate of the Euronext 100 would have an additional impact of 0.2643% on the SCFI.

All equations show that the ARCH term and the GARCH term are statistically significant. It suggests that the shock of volatility today will be passed on to the volatility in the next period, and the impact will last across time. The sum of the ARCH term and the GARCH term is approximately 1, which means the shock does not have such explosive effects. Furthermore, the GARCH term is larger than the ARCH term, indicating that shocks are retained in the variance for longer. This clustering of volatility could predict future volatility in container shipping freight rates.

Table 4. GARCH results for the SCFI

log(SCFI)	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Mean equation	**coef/ (z-statistics)**	**coef/ (z-statistics)**	**coef/ (z-statistics)**	**coef/ (z-statistics)**	**coef/ (z-statistics)**	**coef/ (z-statistics)**	**coef/ (z-statistics)**
log(SCFI[-1])	0.9897*** (367.55)	0.9875*** (17.70)	0.9836*** (163.99)	0.9849*** (183.66)	0.9850*** (184.12)	0.9825*** (194.86)	0.9850*** (184.95)
log(SCFI[-2])		0.0025 (0.04)					
log(Coronavirus _Asia[-1])			0.0099* (1.86)	0.0021*** (2.77)	0.0021*** (2.85)	0.0025*** (3.38)	0.0021*** (2.81)
log(Coronavirus _Europe[-1])			-0.0074 (-1.41)				
Δlog(Oil Price)				0.1960 (0.21)		0.0291 (0.31)	0.0199 (0.22)
Δlog(Stock _Asia)				-0.1437 (-0.09)	-0.0171 (-0.11)	0.0203 (0.13)	
Δlog(Stock _Europe)				0.2659 (1.64)	0.2740* (1.70)		0.2643* (1.69)
Constant	0.1001*** (5.21)	0.0973*** (5.11)	0.1275*** (3.18)	0.1160*** (3.17)	0.1160*** (3.17)	0.1328*** (3.87)	0.1159*** (3.19)
GARCH equation							
Constant	0.000 (-0.13)	0.000 (-0.02)	0.000 (0.03)	0.000 (-0.49)	0.0000 (-0.46)	0.0000 (-0.55)	0.0000 (-0.50)
ARCH	0.4068*** (5.42)	0.4199*** (4.99)	0.2690*** (6.17)	0.2571*** (6.08)	0.2592*** (6.09)	0.2492*** (5.96)	0.2567*** (6.56)
GARCH	0.7226*** (24.00)	0.7097*** (21.52)	0.7905*** (46.36)	0.8010*** (50.85)	0.7997*** (50.16)	0.8046*** (52.30)	0.8012*** (52.57)
Log likelihood	244.3513	236.7338	247.6593	247.2251	247.1791	246.3707	247.2224
Observations	334	324	334	334	334	334	334

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% significance levels, respectively.

5.3 Diagnostics statistics

In order to test the validity of regression analysis when using the GARCH model, it is necessary to check whether the model adequately captures the dynamics of the data. In addition to the stationarity of time series data, another condition of the GARCH model is that volatility clustering must be present in the dataset. The model has to be checked whether it has captured ARCH effects. Furthermore, the data series should also be checked whether it is free from serial correlation (Baum & Schaffer, 2013). There are various of diagnostic statistics can be used to assess the adequacy of dynamic specification. Table 5 shows the diagnostic tests used in this study for testing standardised residuals of each regression model.

The Lagrange multiplier test (LM test) is conducted for the ARCH effect. If the ARCH effect is significantly present in the series, there should be volatility clustering in the dataset. From Table 5, the results for ARCH effects are statistically significant at some degree in each regression model. It indicates that all linear regressions have significant ARCH effects. The Breusch–Godfrey test (Breusch, 1978; Godfrey, 1978) is performed to test whether there is a serial correlation in the residuals of a linear regression. Since the null hypothesis is that there is no serial correlation in the data series, the results must be insignificant in order to ensure autocorrelation does not exist. From Table 5, among equation (4) - (7), only equation (7) shows insignificant effects. It implies that the linear regression has no autocorrelation in the standardised residuals. Since volatility clustering exists, and the standardised residuals in the GARCH model are not autocorrelated, it is suitable to apply the GARCH method to our dataset for equation (7). Compared to other regressions, the conditions of equation (7) are sufficient, making the results more robust.

Table 5. Diagnostic tests for standardised residuals

Regression	**LM test (for the ARCH effect)**	**Breusch–Godfrey test (for serial correlation)**
	chi-squared (p-value)	**chi-squared (p-value)**
(1)	7.242*** (0.0071)	2.868* (0.0904)
(2)	3.811* (0.0509)	6.828*** (0.0090)
(3)	7.030*** (0.0080)	2.009 (0.1563)
(4)	8.228*** (0.0041)	3.562* (0.0591)
(5)	8.910*** (0.0028)	3.891** (0.0485)
(6)	7.601*** (0.0058)	3.258* (0.0711)
(7)	6.354** (0.0117)	1.809 (0.1786)

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% significance levels, respectively.

6. Discussion

From the analysis section, it has been found that the higher the previous value of the SCFI, new confirmed cases per week in Asia, and the growth rate of the Euronext 100, the higher the SCFI in the current period. It is intuitive that the SCFI is strongly dependent on its previous value. According to Tsouknidis (2016) and Michail & Melas (2020), disruptive events would lead to fluctuations in freight rates. The results of our study also suggest that the COVID-19 pandemic has a significant effect on container shipping freight rates. Although a large number of confirmed COVID-19 cases may lead to a bad business environment, our results show that it has a positive relationship with the SCFI. As mentioned in our expectations, this is likely due to an increasing number of port workers testing positive for the COVID-19 pandemic, which forces port closures and straining port systems. Meanwhile, the inefficiency of port handling may also lead to congestions at port. When the port shipments slow down, it can be seen as relatively less space on board for the same cargo demand, and carriers may have to pay more to get a spot on the ship, which will increase freight rates. In addition, it is also possible that after a period of pandemic, the economic recoveries, as well as a large number of stimulus policies and the rise of e-commerce have caused an increase in consumer spending. The sharp increase in demand has led to the shortage of container shipping supply, so freight rates have risen accordingly. These may be the reasons for the rise in freight rates due to the COVID-19 pandemic, but the only certainty is that for the container shipping market, the additional effects of the ongoing pandemic have a greater impact on freight rates than the negative business environment created in the early days of the pandemic.

For the impact of macroeconomic variables on the SCFI, while the Brent Oil Price increases transportation costs, long-term contracts for fuels and lubricants may be the reason why the growth rate of the oil price does not have a significant effect on freight rates, which was also mentioned by Michail & Melas (2020). For container shipping, the Brent Oil Price is only part of the operating expenses. Unlike tankers, oil is a delivered commodity, so its price also affects demand.

Our results show that the growth rate of the Euronext 100 has a significant and positive association with freight rates. This can also be related to the relationship between the stock and shipping markets being stronger during cyclical depressions mentioned by Erdogan et al. (2013). The stock market price can be used as an indicator of the macroeconomic environment, and its rapid changes can reflect industry and consumer activity in real time (Papapostolou et al., 2016; Michail & Melas, 2021). In line with our expectations, the higher the stock price, the better the economic development of the country, which will drive the demand for global seaborne trade. Since this research examines trade lanes from Asia to Europe, European demand is the main driving factor for the shipping market, which may be the reason why the European stock price indicator has a greater impact than the Asian stock price indicator.

6.1 Model comparisons before and during COVID-19 pandemic

If using equation (7) to run the model with the data before 2020 which is before the COVID-19 pandemic and after 2020 when the COVID-19 pandemic starts separately, the results with the data before the COVID-19 pandemic (See Table 6) show that there is a significant positive correlation between the SCFI and its previous value, at 0.7804. However, the magnitude of the effect is not as strong compared to the model with longer period data. The growth rate of the Brent Oil Price and the growth rate of the Euronext 100 do not show significant effects on the SCFI before the COVID-19 pandemic. The ARCH term and the GARCH term are statistically significant in this model. It is also interesting to note that the ARCH term is larger than the GARCH term, which shows different results from the model with longer period data. It indicates that before the COVID-19 pandemic, the volatility today has a larger impact on the volatility in the next period, and it does not persist across time. When checking the diagnostics statistics of the model (See Table 7), the results for the LM test show that the chi-squared is 6.678, and the p-value is 0.0098. When using the 5% significant level, it is statistically significant (p-value = 0.0098 < 0.05). It indicates the presence of significant ARCH effects in the data series. The results for the Breusch–Godfrey test show that the chi-squared is 0.197, and the p-value is 0.6572, which is insignificant. It means that the model has no serial correlation. Therefore, the GARCH method works for this dataset.

On the other hand, when analysing the data after 2020 when the COVID-19 pandemic starts, the series of the SCFI is found to be non-stationary. The results for the ADF test show that the τ_s is -2.482, and the p-value is 0.3371, which is insignificant. Hence, the first-difference is taken to make the series stationary. The results of the GARCH model show that none of the variables have significant effects on the growth rate of the SCFI. Although the ARCH term and the GARCH term are significant in the regression model, the diagnostic tests show that the results for the LM test indicate the absence of ARCH effects, while the results for the Breusch–

Godfrey test indicate the presence of serial correlation in the standardised residuals (See Table 6; Table 7). This implies that the GARCH model has not adequately captured the volatility over this selected time period.

Table 6. GARCH results for the SCFI (models before and during the pandemic)

log(SCFI)/Δlog(SCFI)	**(7) - 1**	**(7) - 2**
Mean equation	**coef/ (z-statistics)**	**coef/ (z-statistics)**
log(SCFI[-1])	0.7804*** (39.59)	
Δlog(SCFI[-1])		0.2316 (1.21)
log(Coronavirus_Asia[-1])		0.0034 (1.41)
Δlog(Oil Price)	0.2375 (1.50)	0.0397 (1.33)
Δlog(Stock_Europe)	-0.1131 (-0.53)	-0.0139 (-0.08)
Constant	1.4849*** (11.20)	-0.0284 (-0.99)
GARCH equation		
Constant	0.0008*** (3.60)	0.0003 (1.17)
ARCH	0.6304*** (3.80)	0.3448** (1.97)
GARCH	0.4376*** (5.82)	0.5934*** (3.07)
Log likelihood	164.8327	145.9748
Observations	244	87

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% significance levels, respectively.

Table 7. Diagnostic tests for standardised residuals (models before and during the pandemic)

Regression	LM test (for the ARCH effect)	Breusch–Godfrey test (for serial correlation)
	chi-squared (p-value)	**chi-squared (p-value)**
(7) - 1	6.678*** (0.0098)	0.197 (0.6572)
(7) - 2	0.440 (0.5071)	21.763*** (0.0000)

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% significance levels, respectively.

Before the COVID-19 pandemic, the results show that there is a significant and positive relationship between the SCFI and its previous value, while the growth rate of the Brent Oil Price and the growth rate of the Euronext 100 do not show significant relationships with the SCFI. It may be because in the usual situation, the macroeconomic environment is relatively stable. In addition to oil prices with less short-term changes due to long-term contracts, stock price movements may come from individual companies rather than reflecting the macroeconomic environment, leaving freight rates unaffected. The data after 2020 when COVID-19 starts does not meet the requirements of the GARCH model. It may be because freight rates are more dynamic after the outbreak of the COVID-19 pandemic, which makes it difficult to capture the characteristics of the volatility. The reason why the results of running the model separately are different from the results of the original model may be that the dynamics of the data for the two periods is different, or it may be that the number of data samples after 2020 when COVID-19 starts is not large enough to perform the analysis.

6.2 Suez Canal obstruction

Due to the strong winds, the container ship Ever Given sailing from Malaysia to the Netherlands was stuck on the Suez Canal on March 23, 2021. The 400-metre-long boat was blocking traffic on the canal completely for one week. The Suez Canal is an important hub for the Asia-Europe shipping route: 12% of the world's maritime shipping passes through it. This obstruction kept over 400 vessels waiting on both sides of the canal, leading to delays in the global supply chain, and forced some shipping lines to detour to the Cape of Good Hope (UNCTAD, 2021b).

The blockage has an adverse effect on the delivery chains, causing an economical damage at somewhere between 2.2 billion and 3.9 billion dollars. In addition, the accident also caused a temporary rise in container shipping freight rates to Atlantic and European destinations (Katsuhisa, 2021). This is because the blockage has exacerbated delays in containership turnaround times, leading to congestion at ports in Europe and elsewhere, thereby exacerbating the shortage of container shipping supply (Katsuhisa, 2021; UNCTAD; 2021b).

6.3 The war between Russia and Ukraine

Political events also influence shipping freight rates by affecting shipping demand (Stopford, 2009). According to Jugović et al. (2015), "Particular characteristics of political development can lead to sudden and unexpected changes in the demand on the shipping market". Political events refer to revolution, local wars, strikes and political nationalisations of foreign properties.

The Russia-Ukraine war in 2022 also affected the shipping market to some extent including shipping freight rates. But different experts have different opinions about how the shipping freight rate was influenced by the war. UNCTAD (2022c) stated that due to the higher fuel cost and zero capacity in maritime logistics, the impact of war in Ukraine can be expected to lead to an increased shipping freight rate. However, global container shipping freight rates seem to have not increased and continue to decrease. UNCTAD (2022c) also explained that it may be due to the easing of lockdown and improvement of port congestion in some areas. They believed that container shipping freight rates would increase soon. While other experts consider that there is less shipping demand and less online orders since people spend money on service again. Hence, the shipping freight rate would decline (Gowans, 2022). Some experts also believe that the downturn of container shipping freight rate is not caused by the war in Ukraine. It is mainly related to a deceleration in demand (ibid).

6.4 Shanghai lockdown in 2022

Container shipping freight rates fell in 2022. Shifl, a technology platform helping shippers plan and manage their supply chain, believed that it was related to the rolling COVID-19 lockdown in major Chinese manufacturing hubs in 2022, especially the lockdown of Shanghai which has the busiest container port in the world (The Maritime Executive, 2022). Factories closure will lead to the reduced goods transported to port and reduce the shipping demand. As a result, shipping freight rates have declined accordingly.

7. Conclusions

This study uses weekly data for a longer sample period from January 2, 2015 to October 8, 2021 to explore the response of container shipping freight rates on the Asia-Europe trade route to the outbreak of the COVID-19 pandemic. The results of the GARCH (1,1) model show that the pandemic outbreak has a strong relationship with container shipping freight rates. More precisely, a 1% increase in new confirmed cases per week in Asia implies an additional impact on SCFI of 0.0021%. It is interesting to note that the pandemic outbreak has positively correlated with container shipping freight rates. This implies that the surge in container demand has increased freight rates more than the pandemic has pushed them down. For macroeconomic variables, including the Brent Oil Price, the Shanghai Composite Index and the Euronext 100, the growth rates of these variables are used in our model. Among these three macroeconomic variables, only the Brent Oil Price, and the Euronext 100 are included in our final model. The Euronext 100 is found to have a significant and positive relationship with freight rates on the Asia-Europe route, with a 1% increase in the growth rate of the Euronext 100 implying an additional impact of 0.2643% on the SCFI. It is also found that the Brent Oil Price does not exhibit any significant relationship with container shipping freight rates. In addition, the results suggest that volatility shocks can last for a long period of time, which is different from the usual situation before the outbreak of the COVID-19 pandemic.

In conclusion, the number of confirmed COVID-19 cases has a significant effect on container shipping freight rates, and macroeconomic variables that can cause short-term fluctuations in shipping demand, such as stock market prices, cannot be ignored. However, since a 1% change in these variables will not cause a big change in freight rates, in addition to considering these variables when forecasting and modelling freight rates, other exogenous events which will affect global seaborne trade should also be taken into account.

Container shipping freight rates on the Asia-Europe trade route have risen ten times the value before the pandemic outbreak. Since container shipping delivers value-added products, consumers are still willing to pay high freight rates. Therefore, despite the increase in container shipping freight rates, the demand for container shipping has not diminished. In addition to the effect of the pandemic, several unpredictable events have an impact on the container shipping freight rates during the period as well. The blockage of Suez Canal in March, 2021 caused a temporary increase in container shipping freight rates. This is due to the increased shortage of containership capacity caused by shipping delays and port congestion. The war between Russia and Ukraine in 2022 also has affected container shipping freight rates, although the maritime community argues whether there is a positive or negative relationship. The lockdown in Shanghai 2022 also has led to a decreased container shipping freight rate because there is a decrease in shipping demand caused by the shutdown of factories in the lockdown area. Since the pandemic is still ongoing, and other major world events affecting freight rates mentioned above have occurred in succession, the estimation of freight rates is more complicated. Therefore, it is hard to say whether freight rates will go back to "normal" again.

Since container shipping has greater market power through alliances, it is more stable and less competitive than the bulk market. However, the results of this study show that fluctuations in container shipping freight rates are seriously affected by the COVID-19 pandemic. Coupled with other disruptive events that happened during the pandemic, it is important for container shipping companies to have the ability to forecast the trends and patterns in freight rates, especially in relation to exogenous shocks, which could help them make more effective decisions about market volatilities and improve their competitive position in the industry. Furthermore, our findings could assist not only shipping companies but also other stakeholders in the shipping industry in reducing the risks of being unprepared for freight rate fluctuations. For ship owners, it could help them make effective speculative investment and momentary decisions for chartering the ship at profitable freight rates. For charterers, they could operate in a cost-effective manner by transporting cargoes at the lowest possible cost. For investors, it could assist them in making the profitable percentage of ship financing and avoiding high financial risks. In addition, since losses from freight rate fluctuations will harm local economics, it could also help policymakers develop corresponding measures.

This study quantifies the impact of the COVID-19 pandemic and macroeconomic markets on freight rates. The findings are representative since it focuses on important shipping markets (container shipping) and shipping trade routes (Asia-Europe), which can establish background knowledge on short-term fluctuations in container shipping freight rates caused by exogenous events for subsequent research. For future research, it can include the updated COVID-19 data to capture the results of this exogenous event adequately, or it can apply our current understanding of exogenous shocks to focus on other particular events during the pandemic. The next time when an exogenous event which causes a similar effect occurs, the model can be applied, such as studying the correlation between the Russian-Ukrainian war and freight rates. In addition, the analysis approach can also be applied in the study on other trade routes, such as the Asia-North America route. Since the GARCH (1,1) model is not able to capture the non-linear structural changes during dynamic fluctuations, future research can also build on the variables covered in this study and apply other innovative multi-technique approaches to provide more accurate forecasts.

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