Did the Suez Canal Blockage of 2021 Raise the Chinese Container Freight Rates?

Author: Qianhui Fang

Advisor: Dr. Patrick Conway

September 20, 2022

The Guest Family Fund Grant for Undergraduate Research in Economics, Summer 2022

The University of North Carolina at Chapel Hill

Abstract

Global shipping flows through strategically important restricted waters such as Panama Canal and Suez Canal, and hence accidents occurring in the canals will cause serious disruptions to global supply chains. Those disruptions could be reflected in higher prices of important commodities like crude oil and gas, significant delays in essential shipments, and additional shipping operation charges. This paper attempts to measure whether the 2021 Suez Canal blockage affects the Chinese container freight rates by applying the OLS model. Our study builds four models to analyze the determinants of container freight rates by organizing those determinants in the supply and demand framework in the market for containers. To measure the impacts of canal blockage, our study treats the date of the blockage as an event so that an event study can explain the increase in freight rate when the supply chain disruptions are taking place. The results show that the Suez Canal Blockage has a long-term effect on increasing the Chinese container freight rates to the European region. However, the blockage does not show significant impacts in raising the container freight rates in the short term.

Keywords: Impact of Blockage; Container Freight Rates; Supply Chain

1. Introduction

Currently, substantial transport volume and low prices have made sea transportation an indispensable transportation mode for international trade. The Review of Maritime Transport (2021) indicates that more than 80 percent of the world's import and export cargo was transported by ships in 2021. Different countries have varied national conditions and industrial systems and thereby varied import and export volumes. This difference generates a complicated international shipping network. Taking China as an example, it has the world's second-largest economy, and it is heavily dependent on import and export trade. The China National Maritime Day Announcement 2022 stated that over 95% of China's import and export cargo is transported by ships, so Chinese container ships have spread throughout the shipping network for import and export transportation. In this international shipping network, canals are seen as the key nodes, and the blockage of these nodes will generate network variations in the major shipping routes. Thus, much attention has been focused on canals; specifically, determining the impact of blockages of the canals on container ships is of great importance. This knowledge is required for managers to develop specific response programs for key canals in advance to reduce the impact of blockages on container ships. Also, having such knowledge could bring more insights into preventing or managing potential exogenous and endogenous shocks to the supply chain and the shipping market. It is therefore urgent to understand how to structure a model that can measure the impact of canal blockages on Chinese container ships.

When one canal is blocked, as happened in the 2021 Suez Canal blockage, all ships will be either stuck in line or forced to reroute, causing significant delays in essential shipments. Freight rates are critical to these ships, as they represent the costs of maintaining normal operations and the results of negotiations between shippers and consignees. Clearly, the longer shipping distance

due to the blockage is one major reason for increased freight rates, but it is not the only one. Measuring the freight rates for container ships in an integrated manner under special conditions of canal blockages is not simple. It is because the canal blockages disrupt the supply chain, introducing an important factor of imbalance between the supply and demand of cargo and container ships. As a result, the freight rate is not predominantly determined by traveling distance but rather by supply and demand in the shipping market. Therefore, the next challenge is how to measure the impacts of canal blockages on freight rates considering these factors.

Based on the above summary, in order to solve the research problem, the impact of canal blockages can be measured by calculating the changes in freight rate by building models and running OLS regressions on actual data. The results of the model are then used to analyze the reasons for the changes in terms of the geographic location of the canal, the shipping route features, and the international shipping market.

The rest of the paper is structured as follows. The next section reviews the literature on canal blockage impacts, textbook determinants of freight rates, and the empirical measure of freight rates. Section 3 describes the methodology and data. The results and analysis are presented in Section 4. A discussion of conclusions, limitations, and future studies is presented in Section 5. The acknowledgment and appendix are included in Section 6 and Section 7 respectively.

2. Literature Review

2.1 Suez Canal Blockage Impacts and Prospects

The Suez Canal, which became operational in November 1869, is one of the world's most vital maritime trading conduits, connecting the Mediterranean Sea to the Red Sea through the Isthmus of Suez and dividing Africa and Asia (ESA 2021). The canal is an essential route of trade

between Europe and Asia. Currently, 12% of global trade and 30% of global container traffic traverse the Suez, transporting over USD $1 trillion worth of goods per annum (Duerr 2021).

However, marine accidents are not common in the Suez Canal even if the canal generally has a good security record. In March 2021, the Suez Canal was blocked for six days after the grounding of Ever Given, a 20,000 TEU container ship (BBC News 2021). Although the Canal blockage of the Suez Canal has been cleared after the incident, it remains an ongoing effect on the global supply chain. More than 300 vessels waiting to pass through the Canal during the blockage were either stuck in traffic or forced to reroute which stopped 12% of world trade from passing through the Canal (Chellel, Campbell and Ha 2021). The backlog of ships carried everything from cattle to crude oil given that almost USD $15 to 17 billion had been held up (Duerr 2021). This contributed to the hike in gas prices on the day of the accident which had increased to USD $ 0.40 in the aftermath of the accident (LeBlanc 2021).

Considering that ships keep coming into the canal, they have to queue at the back of the line given the backlog. Even if traffic has resumed, the backlog has created problems with container availability and ship availability. Countries like the U.S. may experience fewer impacts than European and Asian countries since the U.S. relies on routes through the Pacific to get goods to the west coast and the Panama Canal to the east coast (LeBlanc 2021). In contrast, the Suez Canal is the main artery for shipping between Europe and Asia (Kickham 2021). Europe is the region that will feel the strongest impact due to the blockage of the canal. It is because exports from Asian countries are mostly upstream of the global supply chain, supporting numerous manufacturing sectors in Europe. This poses a risk to supply chains given that this time period is close to the inventory days for many European manufacturers (Segal 2021). Companies located in Asia will be impacted not only by the delay of shipments from Europe but also by a shortage of

empty containers returning to their region. Every week the canal remains closed will require another week to work through backlogs, adding that container shortages would increase by 25% if it takes two weeks for the blockage to be fully resolved (Wen and Yang 2021). This would further stall Asian companies' abilities to deliver goods around the world. Hence, the obstruction shows that one ship can cause enormous and continuous damage to the world economy. Expectedly, there will be an increase in pricing in the shipping industry, especially in maritime transport pricing as the canal blockage exacerbate the supply chain shortage together with the impacts of the COVID-19 pandemic (Kickham 2021).

As a result, a ripple effect for the later three to six months is likely. European ports, already battling congestion since the previous year from exceptional import volumes, now face an onslaught of inbound container ships that will be arriving more or less on top of one another. The time required to process and unload the backlog of ships will further upend the return flow of empty containers to Asia, where they are needed to start the origin leg of much foreign trade activity. Sailing schedules will see significant revisions for the next few months as the sharp wrinkles caused by the Suez Canal blockage are slowly ironed out of global freight networks. Delays, exceptions and even disasters are something that global logistics organizations, including forwarders and third-party logistics, have to contend with regularly in the course of their daily work. But a situation with the far-reaching sea-traffic and commercial trade consequences of this Suez Canal blockage comes on top of a previous year's worth of uncertainty, volatility and cost increases that can only further exacerbate supply chain angst and import/export frustrations (Truelsch 2021).

2.2 Determinants of Freight Rates

To find out the determinants of container shipping rates, it is necessary to first distinguish between container shipping and dry bulk shipping, the two major options for maritime cargo transportation. Container shipping and dry bulk shipping are not substitutes. Container shipments are a form of mass shipping where large quantities of goods are stored in large, metal shipping containers on deck and in the hold of a ship. Container ships usually carry goods such as clothing, machinery, food, furniture, and other freight that can be packaged. These shipments are not a good choice for just-in-time inventory shipments but are often good eCommerce shipping solutions for the B2B business model and those selling wholesale. Dry bulk, or solid bulk, shipping involves the use of bulk storage containers that are stacked and stored on large merchant vessels. The biggest difference between container shipping and dry bulk shipping is the type of goods loaded. Dry bulk goods include anything from wheat and grains to raw materials inventory like wood and coal to finished MRO (maintenance, repair, and operating supply) inventory whereas container shipments only include packaged goods (Georgiev 2019). Dry bulk goods are generally loaded by way of conveyor belts, into cranes, hoppers, or silos. They are shipped on vessels that contain a single deck with multiple hatchways. In conclusion, container shipping carries commodities packaged in containers while dry bulk shipping carries commodities and raw materials.

In this study, our focus is on analyzing the determinants of container freight rates by organizing those determinants in the supply and demand framework. Even though there are differences between container shipping and dry bulk shipping, the factors that can affect both freight rates could be similar under the influences of the international shipping market, such as fuel cost. There are five major demand and supply factors that influence the freight rates in the maritime container shipping market. Supply factors include container availability, truck drivers'

availability, and fluctuations in crude oil price. Some other factors from the demand side include the shipping season and disruptions (SEOK-MIN 1998).

One supply factor is container availability. Container availability is an important factor affecting ocean freight rates. During the peak of the pandemic, the shipping rates are exorbitant because of the unavailability of containers. Container ships are delayed in their schedule due to the lockdown of ports and cities. Those ships have to take a longer distance to a different port to unload goods, leading to delays in returning empty containers. Under increasing demand as the economy starts to rebound after the pandemic, desperate companies wait weeks for containers and pay premium rates to get them, causing shipping costs to skyrocket. On the contrary, if shippers don't have enough cargo to fill an entire container, they will end up paying high freight charges per item shipped. In other words, the marginal cost per item will be high when the containers are not completely filled.

The availability of truck drivers is another supply factor that impacts container freight rates. More specifically, it plays a critical role in determining container shipping capacity. When holiday shipping season arrived, there is an ever-increasing demand for trucks. If the truck drivers' availability is limited, there will be a shortage in moving containers from one point to the next. However, market demand is putting pressure on companies to ship higher volumes. It has forced freight companies to re-price their services in order to hire the already limited truck drivers to guarantee enough containers are transported to the loading ports. Consequently, shippers have to accept their price increases because they have no choices. Before this increase, shippers would have had a variety of lower prices to choose from, but now pricing has increased, and availability has decreased, so there are limited choices. Indeed, the shortage of truck drivers has become a persistent problem in many parts of the globe (Mittal and Udayakumar 2018). This problem has

become all the more pronounced since the COVID pandemic. In the United States, the drivers' shortage has taken the form of a supply chain crisis resulting in empty shelves in the supermarket. The industry has lost 6% of its workers since the pandemic began and struggles to recruit. The industry needs at least 80,000 new truckers, U.S. Xpress, one of the nation's largest truckload carriers, says (Kelly 2022). The road transportation challenges have a direct consequence on the container shipping industry, causing inflation in container freight rates. As freight forwarders need to pay a higher rate to get a trucker to move their shipments to/from the ports, it naturally hikes up the overall shipping costs.

Emergency Bunker Surcharge (EBS) is another important supply factor that accounts for the changes in the crude oil price (Chen 2015). Shipping lines can implement various surcharges whenever they believe it is necessary to do so. Emergency Bunker Surcharge (EBS) is one such charge which addresses the increase in fuel costs. Bunker Adjustment Factor (BAF) is another surcharge that covers the varying costs of fuel costs because of the natural movements in the market. However, the BAF charges are known in advance. The EBS however is implemented as an emergency charge thus one only finds out at the last minute. This leads to sudden changes in the final shipping costs. The EBS could be also applied when the carriers anticipate rising fuel costs. As a result, EBS is charged to cover up the operating losses' of shipping lines under the aspect of rising fuel costs.

One demand factor is shipping season. The container shipping rates depend on the season when manufacturers move the goods. Depending on the season, importers need to pay different rates. For instance, during the high season when there's a tremendous demand for sea freight services, the prices tend to be high. Generally, the peak season runs from July to December. This is the time when manufacturers and exporters/importers start shipping goods to meet the demands

of the holiday season. This is the time when the carriers raise the rates as a response to the increased demand. Additionally, the weeks preceding the Chinese New Year have also come up as a peak shipping season. During this period, manufacturers in the world's second-largest exporting nation, China, rush to move their products. This results in a surge in demand for space as well as freight charges.

Market disruption also play a role. Disruptions include strikes, mechanical breakdowns, trouble with port state control, and collisions. Some of the major risks related to operations of the vessel, which can widely change the scenario of the shipping cycle include ship collision, sinking, piracy, marine disasters, environmental pollution, cargo and property damage resulting in loss, and business interruption. Any of these disruptions impact all supply chains and, subsequently, transportation needs and freight costs. These inefficiencies result in rerouting deliveries, adjusting shipping needs, and further fallout for fulfillment centers working diligently to fulfill orders. These disconnects create obstacles for budgeting and increase freight rates in the final hour.

2.3 Empirical Measures of Container Freight Rate

The determinants of freight rates in the international shipping market have been intensively studied. Past studies usually study freight rates by referencing the Baltic Dry Index (BDI). The Baltic Dry Index (BDI) is a shipping and trade index that measures the average prices paid for the transport of dry bulk materials across more than 20 routes. It is often viewed as a leading indicator of economic activity because changes in the index reflect the supply and demand for important materials used in manufacturing. BDI and Container freight rates are closely related as they move together under the fluctuations in the global shipping market. Therefore, to some extent, BDI and container freight rates can be studied together. Compared with container freight rates, BDI is an

even better index in terms of reflecting changes in the market of supply and demand as BDI is much more standardized and authoritative. In this section, those empirical determinants that impact BDI and container freight rates will be divided into a supply and demand framework and the demand factors will be studied in the Chinese market.

One of the most important supply factors that influence the freight rate is the fuel cost which is represented by Emergency Bunker Surcharge (EBS) explained in the last section. Beenstock and Vergottis (1989) develop a theoretical model for the pricing determination of the shipping market. They consider fuel cost as a key influencing factor from the perspective of operation. Papailias, Thomakos, and Liu (2017) report a positive correlation between the crude oil price and the BDI and then include the crude oil price as a factor in forecasting the BDI. Ruan et al. (2016) apply the multifractal detrended cross-correlation analysis to study the relationship between the freight rate and crude oil prices. They show the cross-correlations between two time-series models are multifractal such that the relationship between freight rates and crude oil price are strongly persistent in a short period and weakly anti-persistent in a long term.

In terms of the demand factors, empirical studies often set the indicators of the global economy, such as GDP growth, to account for changes on the demand side. As the shipping market serves to carry goods for international trade, it is sensitive to the prosperity of the global economy. Ruan et al. (2016) find that ocean freight rates follow an economic cyclical pattern of cycle duration of between 3 and 5 years and that this pattern is relatively stable across time. This empirical finding also demonstrates the effect of overall market demand on influencing ocean freight rates. Kim (2011) investigates how the Chinese economic growth affects the freight rates and claims that the Chinese economic fluctuation is an important factor for the fluctuation of freight rates. In detail, the study finds that the economic trend and the shipping fee, as well as the

economic trend and the trade volume, have unilateral causality. Drobetz, Richter, and Wambach (2012) report evidence that shocks from macroeconomic variables impact the time-varying property of freight rates, indicating macroeconomic variables could better explain and predict the variations in freight rates. Bildirici et al. (2016) find that BDI, gold price, and GDP (Gross Domestic Product) are cointegrated for the United States. Thus, the BDI and gold prices can be used as an indicator for the crisis in GDP growth for the United States.

Empirical studies also find that the financial sector is closely related to the freight rates. Since financial markets function as a barometer for the macroeconomy, the endogenous movements in the financial markets would have an explanatory capacity for the evolution of freight rates. Klovland (2004) and Stopford (2009) argue that the world economic activity is the most important single influence on ship demand and that shipping freight rates are demand driven. Hence an upswing or downturn in the global business cycle is immediately reflected on freight rates. Their study finds that freight rates tend to be higher after increases and lower after stock returns fall. An increase in the S&P 500 returns by 0.11% a month predictably leads to an increase in freight rates of one standard deviation (16.8%). Erdogan et al. (2013) identify the US stock market Dow Jones Industrial Average (DJIA) as a factor influencing BDI using multivariate correlation models. The study finds mutual feedback between the two markets, which becomes stronger during periods of financial turmoil. However, the problem of potential lags exists. It is indicated that changes in BDI help to explain the changes in DJIA in the longer term, while a similar effect is not evident in the short term. Moreover, s significant correlation between BDI and DJSIW (Dow Jones Sustainability Index World) has been detected by Giannarakis et al. (2017). Sartorius and Zuccollo (2018) further show that the correlation between BDI and stock market could be time-varying. Before the financial crisis in 2008, freight rates showed a significant

positive correlation with the ALSI (Johannesburg Stock Exchange All Share Index, South Africa), while after 2008, the correlation became negative. The study concludes that the BDI is only a reliable indicator of future economic activity when the supply of shipping capacity is well matched with the demand.

Other determinants of freight rate are related to the vessel condition and the market for commodities. Factors related to the supply side include vessel types, vessel deadweight, and the world fleet structure. Alizadeh and Talley (2011) show that vessel deadweight and age are important determinants of shipping freight rates at the micro-level, but that changes in the supply side usually take a long time. In terms of the demand side, Sun et al. (2020) address the issue of extreme risk spillovers from the commodity market to the freight market. They report a risk transmission from the oil sector to the maritime market. Angelopoulos, Sahoo, and Visvikis (2020) apply a dynamic factor model to study the relationship between the market for commodities and freight markets. They also find strong economic relationships from commodity to freight markets.

3. Methodology and Data

3.1 Model

The purpose of this study is to develop an empirical model to investigate whether the Suez Canal blockage of 2021 raised the Chinese container freight rates by fitting a simple OLS model. Our study builds models to analyze the determinants of Chinese container freight rates by organizing those determinants into a supply and demand framework in the market for containers. Demand factors include the business cycle of the port of loading, the industrial production of the destination country, the seasonal variation of shipping, and the volatility of the stock market. Supply factor includes crude oil prices. To measure the impacts of canal blockage, our study treats

the crisis date as an event so that the dates can help explain the changes in freight rate when the supply chain disruptions are taking place. Meanwhile, whether the impact of the Suez Canal blockage has a statistically significant effect on increasing container freight rates will be tested.

Based on the variables developed, the paper develops the following econometric model:

$$\ln(P_{it}) = \beta_0 + \beta_1 \cdot \ln(BusiCycle_{it}) + \beta_2 \cdot \ln(IPI_{it}) + \beta_3 \cdot Season_t + \beta_4 \cdot \ln(CrudeOil_t) + \beta_5 \cdot \ln(VIX_t) + \beta_6 \cdot Suez_t + \epsilon_i$$

$i \in$ {West Mediterranean, Europe, West Coast of North America, East Japan}

t = in weeks

3.2 Variable Description

In the model described in Section 3.1, the response variable, the freight rates from the port of loading to the port of destination (P_{it}), are represented by the Ningbo Containerized Freight Index (NCFI). Ningbo Containerized Freight Index (NCFI) refers to the freight index created by the application of the classical price index model. It is used to objectively reflect the fluctuation of freight rates of the international container shipping market by calculating and recording the container freight rates change information of 21 routes departing from Ningbo-Zhoushan port, including composite Index and 21 Indexes of branch routes. The sample data of NCFI are provided by the panel members, which are top freight forwarders with strong route superiority, good reputation, notable impact, and considerable market shares in Ningbo. NCFI is calculated on a weekly bases and the basis period of the NCFI is the 10th week of 2012 (Mar 3rd, 2012 – Mar 9th, 2012), and the basis index is 1,000 points. In this study, the following four routes are selected to investigate the effects of the Suez Canal blockage on the container freight rates:

Table 1: Routes Information

Route	POL	POD
Europe	Ningbo	Rotterdam
W. Mediterranean	Ningbo	Barcelona, Valencia
W. America	Ningbo	Los Angeles, Long Beach, Oakland
E. Japan	Ningbo	Tokyo

One of the demand factors, the business cycle of export trade ($BusiCycle_{it}$) in Ningbo-Zhoushan port, is represented by Maritime Silk Road Trade Index (STI). STI is a set of trade development index systems consisting of import and export trade index. STI is monthly released to measure the level of economic and trade development and reflect the development trend of China's foreign trade in terms of Overall Trade Index, Region Trade Index, and Specific classification Trade Index. The base period of STI is set on March 2015, with a base point of 100. In this paper, Region Trade Index, including Asian Trade Index, European Trade Index, and North American Trade Index, will be utilized to measure the business cycle. One setback of STI is that its value is calculated based on the customs import and export trade data of the current month, whereas our study mainly focuses on studying the export trade of Ningbo-Zhoushan port. Thus, our study assumes that STI is a measure that objectively reflects the development and business trend of export between China and Asia, Europe, North America, and other six continents.

As the business cycle accounts for the trade development and environment of the port of loading, the economic output of the port of destination is another important demand factor that needs to be included. In this paper, the industrial production index (IPI_{it}) is utilized to measure

the economy of the destination port. IPI is a monthly economic indicator measuring real output in the manufacturing, mining, electric, and gas industries, relative to a base year. Thus, IPI can be treated as a macroeconomic indicator to represent the economic trend of the importing country. In this paper, the Industrial Production Indexes of the Netherlands, Spain, the United States, and Japan are used to represent the demand factor for the relative route, Europe, West Mediterranean, West Coast of the United States, and East Japan accordingly.

As mentioned in the literature review part, the shipping season is also a determining demand factor for container freight rates. This paper sets seasonal variation as a set of dummy variables ($Season_t$) in terms of year and month. Since the dataset ranges from January 2015 to May 2022, $Season_t$ is separated into seven columns of year dummy variable (from 2015 to 2021) and eleven columns of month dummy variable (from January to November). The year 2022 and December are left out to avoid the problem of multicollinearity. Take May 21st, 2021, as an example for the dummy variable treatment. For the row with the date May 21, 2021, columns "2021" and "May" take the value 1, and the rest of the sixteen columns all take the value 0. As a result, the significance of seasonal variation in affecting the container freight rates could be better reflected in terms of year and month from the regression summary.

CBOE Volatility Index (VIX_t) is considered another demand factor to account for the changes in the financial sector. As empirical studies find endogenous movements in the financial markets would have an explanatory capacity for the evolution of freight rates, the Chicago Board Options Exchange's CBOE Volatility Index (VIX) will be a representative to track the changes in the stock market. The VIX is a benchmark for measuring the stock market's expectation of volatility based on S&P 500 index options. It's a real-time index that reflects market participants'

expectations of volatility over the next 30 days. Therefore, VIX will count for the impacts of stock market volatility on container freight rate changes.

Sudden increases in fuel cost result in adding Emergency Bunker Surcharge (EBS) on top of container freight rates and thus fuel cost is an essential supply factor determining the changes in freight rates. In this paper, $CrudeOil_t$ is set as an explanatory variable accounting for the price of crude oil. The crude oil price is obtained from the weekly Europe Brent spot price from EIA (U.S. Energy Information Administration). The reason to use Brent crude oil price instead of the price of WTI (West Texas Intermediate) is that the Brent oil price index is a global benchmark used by oil markets which have a larger global reach compared to WTI. Therefore, Brent crude oil price is a more common representative of the global crude oil market in the study of ocean freight rates.

The last variable that accounts for the disruption on the demand side is the crisis variable, $Suez_t$. This is the main variable that this paper attempts to test for its significance in the regression. Similar to $Season_t$ which accounts for seasonal variation, $Suez_t$ is also a set of dummy variables that take the value of 0 and 1 which denotes the time periods after the Suez Canal blockage takes place. As the ripple effect of the canal blockage is likely to remain for three to six months, this paper divides the crisis variable, $Suez_t$, into seven dummy variables that represent seven time periods after Mar 23rd, 2021 (the date of blockage), from one week, one month, two months…to six months. In other words, $Suez_t$ is an exogenous variable that catches differing time periods after the blockage. Each period will enter separately into regression and the resulting coefficient picks up the average weekly blockage impacts on the freight rates. As a result, the significance of different duration of the Suez Canal blockage's effects on container freight rates could be tested in an OLS regression model.

3.3 Data Processing and Statistical Techniques

In the final dataset, our study obtains 383 rows of observation, representing 383 weeks with a time frame ranging from Jan 2nd, 2015 to Apr 29th, 2022, and 30 demand and supply variables. The dependent variable, container freight rates (P_{it}), is calculated on a weekly basis whereas the business cycle ($BusiCycle_{it}$) and industrial production (IPI_{it}) are calculated monthly. We used the method of linear interpolation to construct new data points to fill out the missing values within the range of a discrete set of known data points. As a result, we transform the monthly data into weekly. The stock market volatility (VIX_t) is originally measured on a work-day basis. So, we calculate the weekly stock market volatility by taking the mean of the VIX of that week so that we can have one observation per week. After data interpolating and manipulating, all explanatory variables are entered into the dataset on a weekly basis. For the purpose of regression and interpretation, our study also takes the natural log of all quantitative variables, including container freight rates (P_{it}), business cycle ($BusiCycle_{it}$), industrial production (IPI_{it}), stock market volatility (VIX_t), and crude oil price ($CrudeOil_t$). Using logarithmic transformation, we can see the percent change rather than the unit change which is more intuitive for interpreting and spotting relationships between the dependent variable and explanatory variables. Also, as our research focuses on a time-series dataset and the distribution of data is not normalized, logarithmic transformation improves the fit of the model by transforming the distribution of the features (Feng et al. 2014).

3.4 Result Hypotheses

Our study will conduct the OLS regression on the container freight rates of four different routes, from Ningbo-Zhoushan port to West Mediterranean, Europe, West Coast of North America,

and East Japan, based on the variables mentioned above. The two routes to the West Coast of North America and East Japan are designed as control group. It is because the container shipments to these destinations will not pass through the Suez Canal. The United States relies on routes through the Pacific to get goods to the west coast and the Panama Canal to the east coast. Japanese shipments even take a much shorter Pacific route, passing through the south of the East China Sea and the Sea of Japan. Thus, we expect the effect of the Suez Canal blockage will not have a significant effect on increasing the container freight rates for those two shipping routes. In other words, the crisis variable ($Suez_t$) for different time periods will not have a statistically significant correlation with changes in freight rates for shipments to the West Coast of North America and East Japan.

The two routes to the West Mediterranean and Europe are designed as treatment group. In contrast to the Pacific routes, the Suez Canal is the main artery for shipping between Europe and Asia. As mentioned in the previous section, the blockage exacerbates the global supply chain shortage, leading to a series of ripple effects on the ocean freight market. As a result, we expect the effect of the Suez Canal blockage would have a significant effect on increasing the container freight rates in the long run for the Suez Canal shipping routes. Its effect might not be obvious for the first week. However, we believe that its effect would perpetuate for months, and as time goes on, the problems of the strained supply chain could be directly reflected in the continuous increases in the freight rates. In other words, we expect the crisis variable ($Suez_t$) for three to six months after the blockage will have a statistically significant correlation with changes in freight rates for shipments to the West Mediterranean and Europe.

For the rest of the variables, we expect the business cycle ($BusiCycle_{it}$) has a strong positive relationship with the container freight rates for all four routes. It is because the business

cycle represents the boom and bust in the business of Chinese ports. Demand would increase when the trade is in the boom period. The increase in the need for exports and imports leads to higher freight rates due to limited container and ship availability. We also expect the total industrial production (IPI_{it}) might have a positive relationship with the container freight rates for all four routes. As the IPI_{it} represents the economic condition of the destination country, when it is high, a country would have more goods to be traded. As a result, the carriers would raise the rates as a response to the increased demand. However, it is possible that total industrial production has no statistically significant relationship with container freight rates. One probable reason is that industrial production cannot be weighted equally to the business cycle of the port, as the latter plays a more important role in determining the container freight rates while the former is just a general macroeconomic indicator. For stock market volatility (VIX_t), we expect it will have a relatively low or no significant impact on the container freight rates for all four routes. Empirical measures suggest a correlation between the movements of the financial sector and the container freight rates instead of regarding the former as a determinant of container freight rates. Thus, it is highly possible that the stock market volatility does not influence the container freight rate significantly.

For shipping season ($Season_t$), we expect January and the months from July to December have a strong positive relationship with the container freight rates. As mentioned in the literature review section, the peak season for four routes runs from July to December. This is the time when Chinese manufacturers and exporters/importers start shipping goods to meet the demands of the holiday season, particularly for Christmas. Also, the month preceding the Chinese New Year is also regarded as a peak shipping season. Those peak months result in a surge in demand for container spaces as well as freight charges. Reasonably, we would expect the non-peak months,

from March to June, to have a negative or no relationship with the container freight rates due to relatively lower demand.

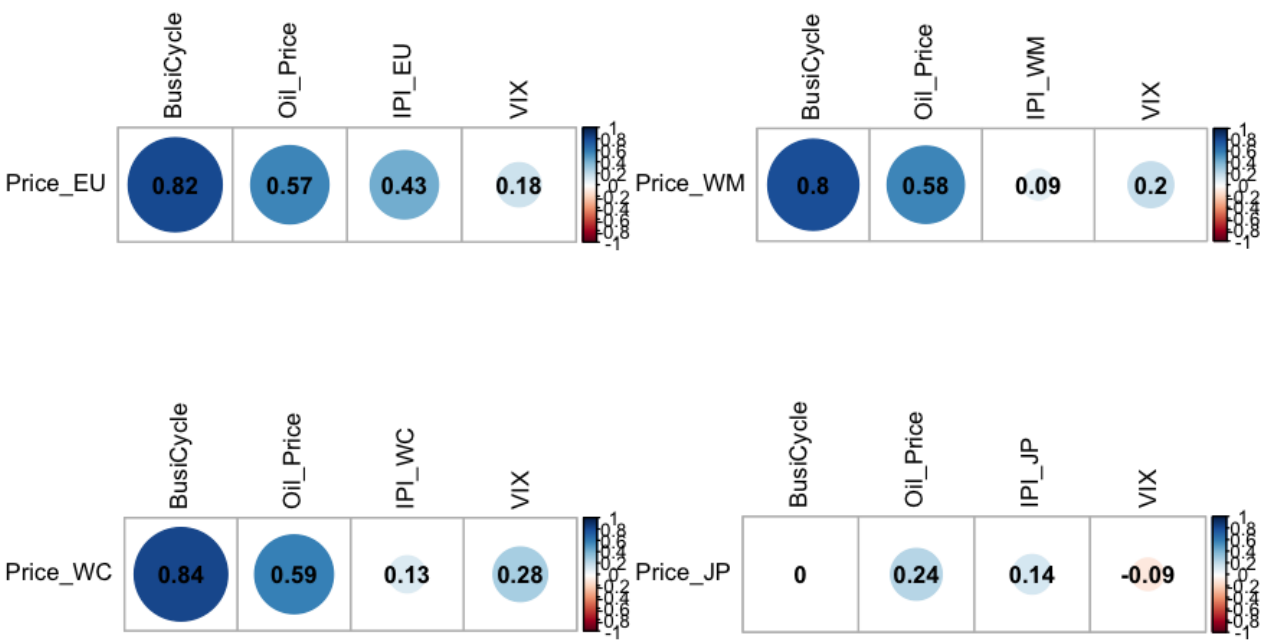
Lastly, for the price of crude oil ($CrudeOil_t$), we expect there is a positive relationship between the Europe Brent spot price and the container freight rates. Past empirical studies prove that crude oil price is one of the most important elements in forecasting freight rates and thus we anticipate an increase in crude oil price leads to a statistically significant increase in freight rates.

4. Results and Analysis

4.1 Correlation between Quantitative Variables

Figure 1 illustrates the correlation between the freight rates of each route and the other four quantitative variables, including the business cycle, oil price, total industrial production of the destination country, and VIX. Price_EU, Price_WM, Price_WC, and Price_JP on the plot stand

Figure 1: Correlation Plot



for the container freight rates from China to Europe, the West Mediterranean, the West Coast of the United States, and East Japan.

From the correlation plot, except for the East Japan route, other routes have a strong positive correlation between the container freight rates and the business cycle. Each correlation coefficient achieves a value bigger than or equal to 0.8, indicating their relationships are strong. For Japan, the value 0 reflects that there is almost no direct correlation between container freight rates to Japan and the business cycle. The crude oil price appears to have a moderate or weak positive relationship with container freight rates as each correlation coefficient is around 0.6 except for Japan. One possible reason for Japan's exception is that there is a much shorter sea distance between China and Japan compared to the other three routes so an increase in fuel costs does not lead to a significant increase in freight rates. In terms of total industrial production, only the freight rates to Europe appear to have a moderate positive relationship with industrial production. The other three routes only show a weak positive correlation between the two. VIX has a weak positive relationship, with a correlation coefficient of around 0.2, with the freight costs for all three routes except for the East Japan route. It suggests that the financial market volatility does not strictly co-move with the changes in freight rate in our dataset.

However, high correlation between the dependent variable (freight rates) and each explanatory variable (four quantitative variables) does not guarantee the significance of the explanatory variable from a statistical perspective. It is likely that the explanatory variable is not significant in influencing the dependent variable even if they are highly correlated. There might be other variables that confound the relationship. Therefore, we need to take other variables into account and look at the marginal effect of each individual variable on the dependent variable by fixing other explanatory variables. As a result, the above correlation analysis is not conclusive as

it only provides a general view of the variable pattern. We will examine whether the explanatory variable is significant in influencing the dependent variable in the regression part.

The correlation within four quantitative explanatory variables is also examined in this paper. Figures 2-5 in the Appendix section illustrate the correlation between four quantitative explanatory variables for each route. A relatively strong correlation between variables is demonstrated in the diagonal which is worth noticing. A moderate positive relationship between the business cycle and crude oil prices is a pattern shared by all four routes. Crude oil prices appear to have a strong correlation with the total industrial production except for the route to Japan. Moreover, a moderate negative correlation between the total industrial production and VIX is also shared by all four routes, indicating an increase in stock market volatility is accompanied by a decrease in industrial production. The rest of the variables does not exhibit a significant correlation with one another so we will not talk about them in detail here.

The above analysis of quantitative variables is based on the bilateral correlation in the dataset without considering other variables. There might be problems of multi-collinearity. Therefore, the results are not conclusive. We will explore more in the model regression part.

4.2 Correlation between Container Freight Rates and Crisis Variable

Table 2: Correlation between Price and Crisis Variables

	Price_EU	Price_WM	Price_WC	Price_JP
one_week	0.046	0.046	0.035	-0.027
one_month	0.127	0.133	0.085	-0.069
two_month	0.231	0.234	0.149	-0.098
three_month	0.321	0.314	0.202	-0.119
four_month	0.410	0.390	0.260	-0.134
five_month	0.491	0.458	0.330	-0.153
six_month	0.581	0.545	0.413	-0.152

Table 1 shows the correlation between the freight rates of each route and crisis variables. As mentioned in the Variable Description section, our study divides the crisis variable into seven periods. Looking vertically, the table shows a trend of increasing correlation between the crisis variable and the container freight rates. For six months after the Suez Canal blockage, the correlation coefficient attains its highest value for each route. The Europe route and the West Mediterranean route almost share the same rate of increase. For the first week, the canal crisis does have a significant impact on the freight rates. Over time, as the ripple effects of the blockage start to bring negative influences on the already disrupted supply chain, the crisis variable and the overall container freight rates start to relate closer together.

We also find that the freight rates for the West Coast of the United States have a moderate positive correlation with the crisis variable. And the correlation coefficient increases over time which is the opposite of what we initially expected. The route to the West Coast of the United States is considered a control group so we expect the freight rates will not be strongly correlated to the blockage period. However, we should not attribute the cause of this high and increasing correlation to the Suez Canal blockage. It is because the West Coast route was hit by bottlenecks exacerbated by the COVID-19 pandemic. Another reason is the shipping backlogs at the ports of Los Angeles and Long Beach, and the resulting goods shortages and price surges. Backlogs and elevated shipping costs persist for months without an immediate solution for the underlying supply-demand imbalance at US ports. Thus, it is reasonable to find an increase in US container freight rates at a time when the Suez Canal crisis starts to impact the global supply chain. As expected, the freight rates for Japan do not have a positive relationship with the crisis periods. It is because shipping routes from China to Japan do not go through the Suez Canal so the crisis period should have a weak relationship with the freight rate of Japan.

Again, correlation does not indicate causation or statistical significance. We need to take other demand and supply variables together with the crisis period to evaluate the significance of different crisis periods in influencing container freight rates. The model regression part will do a more concrete analysis.

4.3 Model Regression Results

As mentioned in the data processing section, before conducting regressions, our study takes the natural log of all quantitative variables, including container freight rates (P_{it}), business cycle ($BusiCycle_{it}$), industrial production (IPI_{it}), stock market volatility (VIX_t), and crude oil prices ($CrudeOil_t$). Then, we regress the container freight rates of each route on the business cycle, industrial production of the destination country, the seasonal variation of shipping, VIX, crude oil prices, and each crisis period. In this section, we discuss the regression results of four routes. Our main focus is on testing the influence of the Suez Canal blockage on increasing the container freight rate. At the same time, we evaluate and compare the results to past studies that focus on studying the determinants of freight rates. Also, we do minor adjustments to the event variable in the regression to explore more of the marginal effects of the Suez Canal blockage by month or by different routes.

In the following part, we explore four types of regression models to examine how the Suez Canal blockage would have an impact on container freight rates from multiple perspectives. Model 1 is a general model with a different even horizon approach that explores the weekly average impacts of different event periods, from one week to six months, on the container freight rates for each route. Model 2 looks at the marginal effect of each month of the blockage on the container freight rates for all four routes by running multiple times of regressions relative to individual

months. Model 3 makes further adjustments to Model 2 in terms of the regression method. We run one regression for every route with all of the monthly marginal effects included at once, along with other exogenous variables. All individual months are counted as separate regressors in that one regression for each route. Model 4 is different from the other three models. Model 4 tests the hypothesis of this paper that the Suez Canal blockage would raise the container freight rates for the European region but not for the U.S. West Coast and East Japan. The regression of Model 4 runs on a stacked dataset where the treatment group and control group are aggregated together. We will discuss the differences between each model and the interpretation of each regression results in more detail in each model section.

Model 1: Multiple Regressions with Different Event Horizon

Model 1 is the initial model that regresses the container freight rates of each route on each event period along with other exogenous variables, including business cycle, industrial production, stock market volatility, seasonal variation of shipping, and crude oil prices. We run seven regressions for each route on each event period, leading to twenty-eight regressions in total.

From the regression output of the freight rates model of all four routes (see Table 3-6 in the Appendix), the significance of crisis period variables varies. For Europe, the first four months of the blockage period are not statistically significant in influencing the container freight rates and some of the coefficients have a negative sign. However, the crisis periods of five months and six months turn out to be statistically significant in raising the freight rates. An increase in one week of the five-month and six-month blockage period leads to a 0.164 percent and 0.26 percent change in freight rates to Europe respectively. This pattern reveals that the Suez Canal blockage does not have a large effect on changing the freight rates of Europe immediately whereas its effect would

be reflected in the shipping cost in a long term. The West Mediterranean route shares a similar pattern with Europe. The first five months of the crisis variable are not statistically significant while the period of six months shows relatively strong significance. An increase in one week of the six-month blockage period leads to a 0.174 percent change in freight rates to West Mediterranean. As Europe and West Mediterranean are in the treatment group and the crisis variables have a significant impact on the shipping cost in the longer term, the finding confirms the previous study suggesting that the ripple effect of the canal blockage would last for three to six months in the European region. For the control group, the routes of the U.S. West Coast and East Japan give very different outputs for the crisis period. The output for the U.S. West Coast suggests that none of the crisis period variables are statistically significant in raising the container freight rates, which is within our expectations. However, the crisis periods appear to have a significant negative relationship with the container freight rates, indicating that the freight rates to Japan continue to decrease during those six months.

As expected, for all four routes, the p-value for the business cycle is lower than the significance level of 0.05, confirming that the business cycle is one of the most significant determinants of freight rates. The coefficients are elasticities and, since it is positive and greater than 1, we consider the business cycle has elastic effects on container freight rates. A 1 percent increase in STI (Maritime Silk Road Trade Index) leads to an approximately 1.2 percent increase in freight rates. The higher the demand for imports and exports, the higher the freight rates. Moreover, the coefficients of the business cycle fluctuate around 1.2 for all three routes except for the route to Japan, which has coefficients of around 0.75.

In terms of fuel cost, Europe, West Mediterranean, and the U.S. West Coast routes show a significant and positive relationship between freight rates and crude oil prices. Looking at the row

of Oil_Price, the elasticity of crude oil prices for the route to Europe shows a steadily increasing trend from 0.324 to 0.378, indicating that a 1 percent increase in crude oil price leads to a greater change in container freight rates as the duration of the blockage effects becomes longer. For the U.S. West Coast route, the elasticity of crude oil prices remains constant at around 0.21, indicating that crude oil prices always have a relatively small positive influence on the freight rates regardless of the canal blockage. For the route to the West Mediterranean, the elasticity of crude oil prices fluctuates around 0.68 among all crisis periods, which has a higher impact on container freight rates compared to Europe and the U.S. West Coast routes. In contrast, the route to Japan does not show a statistically significant relationship between the two, and the crude oil prices appear to be very inelastic due to low coefficient values.

Moreover, the total industrial production correlates with the container freight rates differently across four routes. The destination country's IPI appears to have no significant influence on freight rates for shipments to Europe, the U.S. West Coast, and Japan. Regardless of the significance of coefficients, a 1 percent increase in Europe IPI leads to a decreasing trend in percentage increase in freight rates as the duration of blockage becomes longer. For the route to U.S. West Coast, a 1 percent increase in the United States IPI leads to a 1.5 percent increase in the freight rate. However, in contrast to the route to Europe, the coefficients for U.S. IPI appear to have little variation across all crisis periods. For the route to Japan, Japan's IPI is surprisingly negatively related to the freight rates even though the relationship is not significant. Nevertheless, IIP has a statistically significant negative relationship with freight rates for the West Mediterranean route which is unexpected. A 1 percent increase in the West Mediterranean IPI leads to a 1.3 percent decrease in the freight rate, reflecting that West Mediterranean IPI has an elastic effect on the freight cost.

Almost all four routes reveal that VIX does not have a statistically significant relationship with the container freight rate except for the coefficient of month_five and month_six in the route to the U.S. West Coast. Similar to the results in the correlation analysis section, without considering the issue of variable significance, VIX exhibits a weak positive relationship with the container freight rates for three routes except for Japan, where there is a weak negative relationship between the two. This finding reflects that the stock market volatility is not closely related to the freight costs or can be considered as one of the determinants of it.

For shipping season, the output of three routes, except for Japan, confirms that January and February are two peak months that drive the demand and also freight rates up. It confirms the result of past studies that there is a higher demand for shipping preceding the Chinese New Year. For those three routes, an increase in one week in January or February leads to a 0.2 percent increase in freight rates on average. Even though these coefficients are not elastic as they are below 1, their strong statistical significance suggests that an increase in freight rates during January and February is robust. The negative coefficient of months between March and June also indicates those months are off-season with low demand. One thing that is also worth noticing is that, for the shipments to the U.S. West Coast, container freight rates exhibit an increasing trend between August and November. This finding again confirms that exporters/importers start shipping goods to meet the demands of the holiday season.

Model 2: Multiple Regressions with Monthly Marginal Effect

As Model 1 suggests that the Suez Canal blockage has a long-term effect on increasing the container freight rates for the European region, it gives us an incentive to look at the monthly marginal blockage effect on the container freight rates. Therefore, we build Model 2 to explore the

marginal effect of each month of the blockage on each route's freight rates. We make some minor changes in the crisis variable. Instead of separating the crisis variable into continuous months, we separate the crisis period into individual months. As the first month after the blockage may have the most obvious increase in container freight rates, we divide the first month into two periods, the first two weeks and the second two weeks. Then we have the second month, the third month, …until the seventh month. We add one more month, the seventh month, compared to the original model because we intend to look at whether the blockage still raises the container freight rates after the predicted period of three to six months of ripple effects. Moreover, our new model only changes the design of the crisis period. All the other variables and the formula for the regression stay the same.

From the regression results in the Appendix section (Table 7-10), we find that most periods of the crisis variable still appear to have an insignificant relationship with the container freight rates within the European region. Routes to Europe and the West Mediterranean shared a similar pattern revealed by the coefficients of the crisis period. All coefficients of the first six months of the crisis period are insignificant. It reflects that the Suez Canal blockage does not have a strong marginal effect by month on increasing container freight rates to Europe and the West Mediterranean. There might be other factors that induce the increase in freight rates, such as the ongoing supply chain shortages. However, the coefficient of the seventh month of the blockage is statistically significant for both routes, indicating that the seventh month after the blockage has a positive relationship with the container freight rates in the European region. An increase in one week of the seventh month of the blockage period leads to an about 0.37 percent change in freight rates for both routes. Except for the changes in significance in the crisis period, all the other

variables have similar results to the original regression, only having minor changes in the value without changing signs and significance.

Model 3: Single Event Regressor per Route

Model 1 and Model 2 give us similar regression results, showing that the short-term average weekly increases in container freight rates in the European region are not significant. The blockage only has a significant effect on weekly freight rates if we set the event period to six or seven months. So, in Model 3, we make further adjustments to Model 2 in terms of the regression method. We run one regression for every route with all of the monthly marginal effects included at once, along with other exogenous variables. All individual months are counted as separate regressors in that one regression for each route. In that case, the coefficient for each month of the blockage represents the weekly percent increase in the container freight rates in that specific month.

From the regression output (Table 11 in the Appendix), we find that the event periods appear to be more significant in Model 3 compared to previous models. To better visualize the trend of weekly percent change in the container freight rates, Figure 6 illustrates the event coefficients for the route to Europe and the West Mediterranean. Each point represents the weekly percent increase in the container freight rates in that specific event period. Statistically significant coefficients are marked in red.

For the route to Europe, even though the first two months do not show a significant increase in freight rates, from the third month to the seventh month, the weekly increases in container freight rates due to the canal blockage are statistically significant. For month_3 to month_5, an increase in one week of the blockage leads to an approximately 0.37 percent change in freight rates to Europe. Starting from the sixth month, the percent increase in weekly freight shows an increasing

trend. For the sixth month, an increase in one week of the blockage leads to a 0.409 percent increase in freight rates, while for the seventh month, the number raises to 0.53. This pattern reflects that the Suez Canal blockage impacts tend to permeate and accumulate over time. Its influences on raising the freight rates to Europe are reflected in a long term instead of immediately.

Figure 6: Event Coefficients for Europe and the West Mediterranean Routes

However, for the route to the West Mediterranean, the blockage does not significantly impact the container freight rates for the first five months. Even though the value of the coefficients exhibits an increasing trend over all seven months as we can tell from Figure 6, only the coefficients of the last two months appear to be significant. It is surprising that even if we include

all monthly marginal effects at once, the significance of each crisis period does not experience an obvious change. This finding further consolidates the conclusion that we drew from the regression results of the route to Europe that the Suez Canal blockage does have an impact on the container freight rates to the European region in the long term, whereas the impacts cannot be reflected immediately on the container freight rates in the first two months.

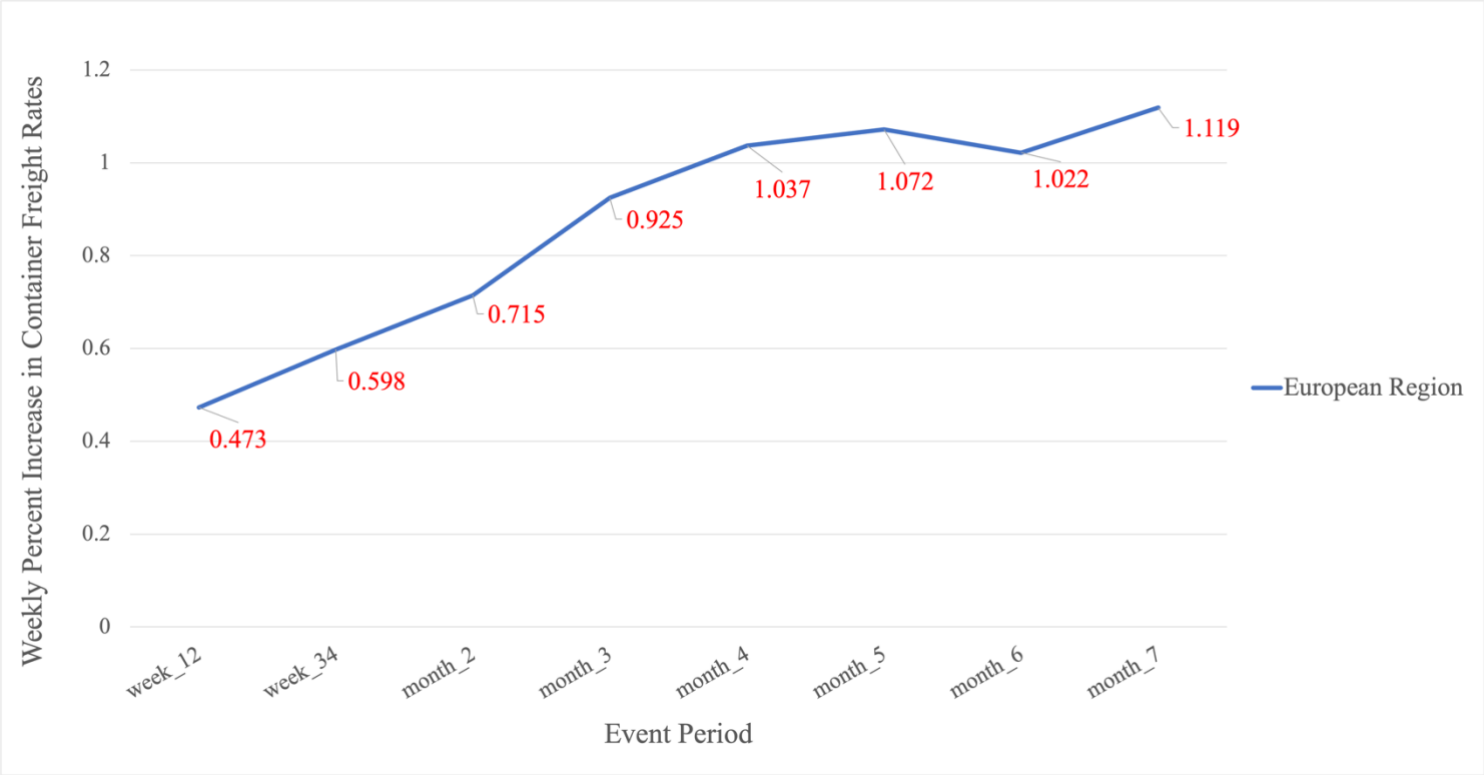
The other exogenous variables' coefficients and significance are similar to the regression results of Model 1 and Model 2. As we talked about them in detail in previous model sections, we will not explain them in detail here. We only focus on exploring the changes in event variables for the two European routes in Model 3 and so does the same for Model 4.

Model 4: Complete Hypothesis Test on Aggregated Data

In the previous three models, we run separate regressions on each route to explore how the blockage influences the freight rates in different event horizons or different regression methods. In Model 4, we tend to test our initial hypothesis that the Suez Canal blockage raises the overall container freight rates in the European region, having the other exogenous variables fixed at the same time. Unlike the previous model in which we divide the control group and treatment group to run separate regressions, we will have the data for each route aggregated on top of each other into a stacked matrix for Model 4 regression. As our goal is to see how the European freight rates respond to the crisis, we create another dummy variable $Effect$ to denote whether this route is to the European region. In that case, $Effect = 1$ if the route is to Europe or the West Mediterranean, and $Effect = 0$ if the route is to the U.S. West Coast or East Japan. In the regression model, we have all the event periods multiplied by the variable, $Effect$, creating a list of interaction terms, such as month_1:effect in the table of regression results, to substitute the original event variables.

Thus, those interaction terms will be one of the regressors for the route to the European region. Conversely, the interaction terms will not join the model for the route to the U.S. West Coast and East Japan as their value for $Effect$ equals zero, leading to a value of zero for interaction terms. In short, for Model 4 regression, we regress the stacked freight rates of four routes on interaction terms and all the other same exogenous variables that are also in an aggregated fashion. As a result, the coefficients of interaction terms merely reflect the weekly average percent change in the European freight rates and have nothing to do with other routes' freight rates.

Figure 7: Coefficients for the Interaction terms



From the regression results of Model 4 (Table 12 in the Appendix), all the coefficients of interaction terms are statistically significant. It proves that our initial hypothesis is true that the Suez Canal blockage does raise the overall container freight rates in the European region. Not only

those coefficients are significant, but they also show an increasing trend in Figure 7. The European container freights experienced a weekly 0.472 percent change for the first two weeks after the canal blockage takes place while the weekly percent change raises to 1.119 by the seventh month. This finding also reflects that the impacts of blockage permeate over time and become more evident in the level of increases in freight rates.

Besides interaction terms, other exogenous variables appear to be significant as well. The coefficients for the business cycle, crude oil prices, and total industrial production are significant. The coefficient value of 0.910 for the business cycle suggests that the business cycle has a strong positive relationship with the container freight rates and can be taken as one of the determinants of the freight rates. Even though the oil price is significant, the coefficient is negative. The negative sign might be influenced by the route to Japan in the aggregated data, as the price increase in crude oil does not have a significant impact on the container freight rates to Japan due to the relatively short distance from China to Japan. It is surprising to see that the coefficient for total industrial production is significant in Model 4 regression. In previous models, IPI appears to be not significant or has low significance. The coefficients for stock market volatility and the seasonal change do not show strong evidence to influence the container freight rates. However, Model 4 only has a value of 59.1 for R^2 which is much lower than the three previous models. It means that Model 4 can only explain 59.1 percent of the variation in the container freight rates. Thus, it is entirely possible that stock market volatility and seasonal change are potentially significant, but Model 4 does not fairly reflect that due to a lack of model explanatory power.

5. Conclusion

This paper investigates whether the Suez Canal blockage of 2021 raises the Chinese container freight rates. Using weekly data of four shipping routes (Europe, the West Mediterranean, the West Coast of North America, and East Japan), we regress the container freight rates of each route on the business cycle, total industrial production of the destination country, the seasonal variation of shipping, stock market volatility index, crude oil prices, and event period. It is found that the Suez Canal Blockage has a long-term effect on increasing the container freight rates for the European region. However, the blockage does not show significant and immediate impacts in raising the container freight rates in the short term. Our regression results also confirm the conclusions drawn by empirical studies that the business cycle and seasonal variation have significant influences in determining container freight rates. And the crude oil prices have a strong positive relationship with freight rates for longer-distance shipments.

However, this study has several limitations. First, due to limited access to Chinese shipping data, especially for the Ningbo-Zhoushan port, we only have an overall trade index, which integrates import and export trade, to measure the business cycle of the Chinese shipping market. Yet, our study mainly focuses on studying the export trade of Ningbo-Zhoushan port. Thus, the data used for counting the business cycle could not be representative of the export trade. Second, the COVID-19 pandemic of 2020 still has a great impact on the global supply chain even after one year. The container freight rates skyrocketed on a global scale due to the severe supply chain shortage resulting from the pandemic and the increasing trend does not seem to decline or even cease in 2021. Therefore, the impacts of the canal blockage on the container freight rates might be masked by the impacts of COVID, or the statistically significant impacts of the blockage that we find are indeed the continuing negative influences of the pandemic. Third, the West Coast of North

America is not the best choice for the control group. From the correlation analysis, we can find that the West Coast route exhibits a continuous increase in container freight rates during the blockage period even though the U.S. should be relatively free from the impacts. This is due to the shipping backlogs at the ports of Los Angeles and Long Beach. Demand for goods outstripped the capacity to unload containers due to labor shortages resulting from the pandemic. Container ships were waiting to unload and thus causing congestion in ports. The freight rates increase because of the accumulating surcharges on ocean carriers with containers overstaying. Therefore, the West Coast route is not an ideal control group as the freight rates increase as well during the blockage period even if this route is free from the blockage impacts. Lastly, from the regression results of Europe in Model 1, we find that the coefficient of IPI decreases from 1.132 to 0.226 as the crisis period becomes longer. However, the coefficients of IPI stay relatively constant or involve little fluctuations for the other three routes. Moreover, in Model 4, IPI shows strong statistical significance in the regression output for the aggregated dataset, whereas IPI does not appear to be significant in previous model regressions when each route is regressed separately. There must be some reasons to explain those disparities while they are out of the research scope of this paper.

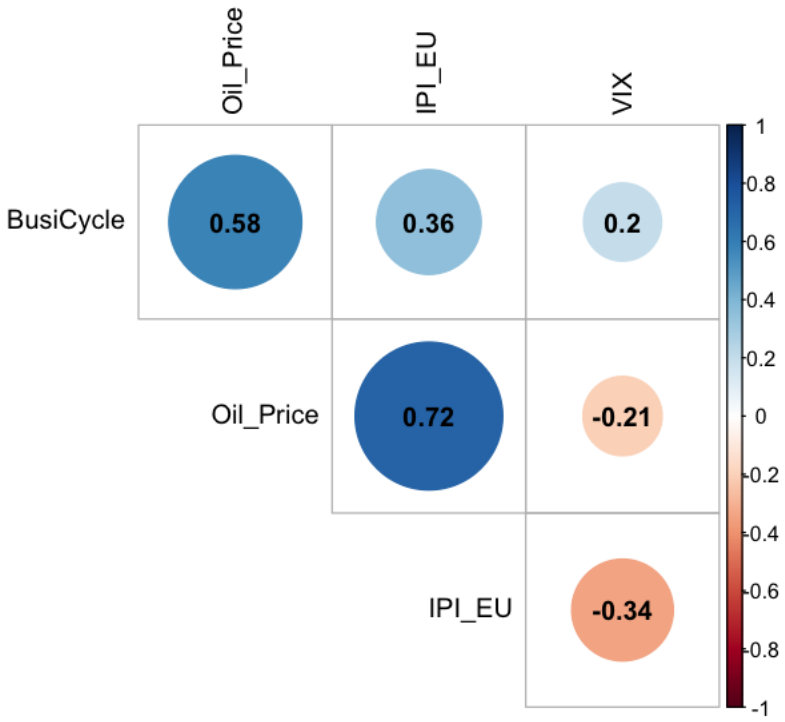
Given the complexity of the components of container freight rates, more research is needed to explore further the impacts of the Suez Canal blockage on the container freight rates. For example, consider adding more shipping routes to the dataset to examine the global impacts of the blockage disruption. Or, exploring more explanatory variables and adding them to the regression to account for the changes in freight rates. In addition, it is also recommended for future studies to exclude the impacts of the COVID-19 pandemic and the resulting supply chain shortage if want to examine one incident's impacts on freight rates.

6. Acknowledgment

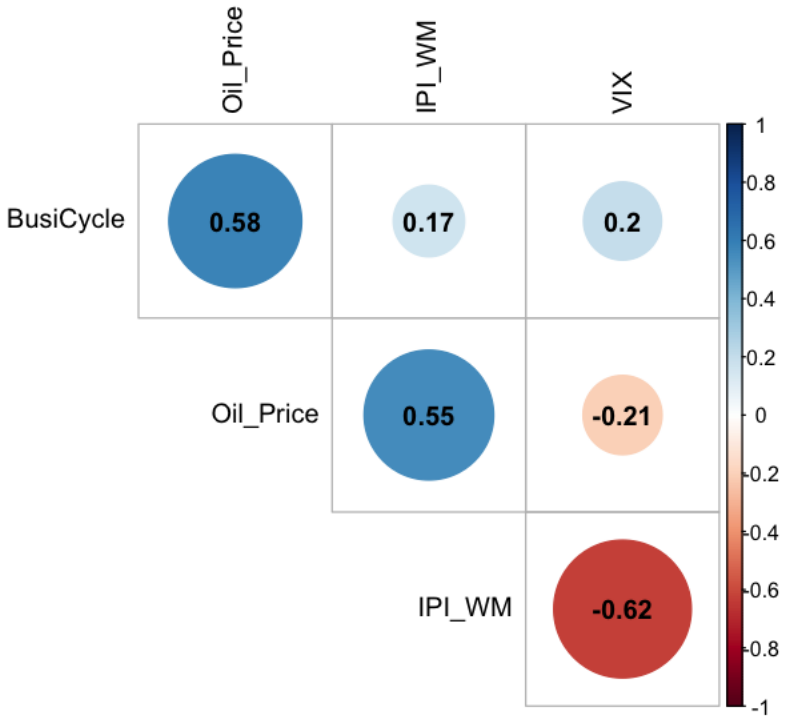
I would like to express my appreciation for the research opportunity provided by the Matthew Guest Family Fund Grant for Undergraduate Research in Economics and the UNC Economics Department. I would also like to show my deep appreciation to my supervisor, Dr. Patrick Conway, for all suggestions and guidance that offered me to finalize my research project.

7. Appendix

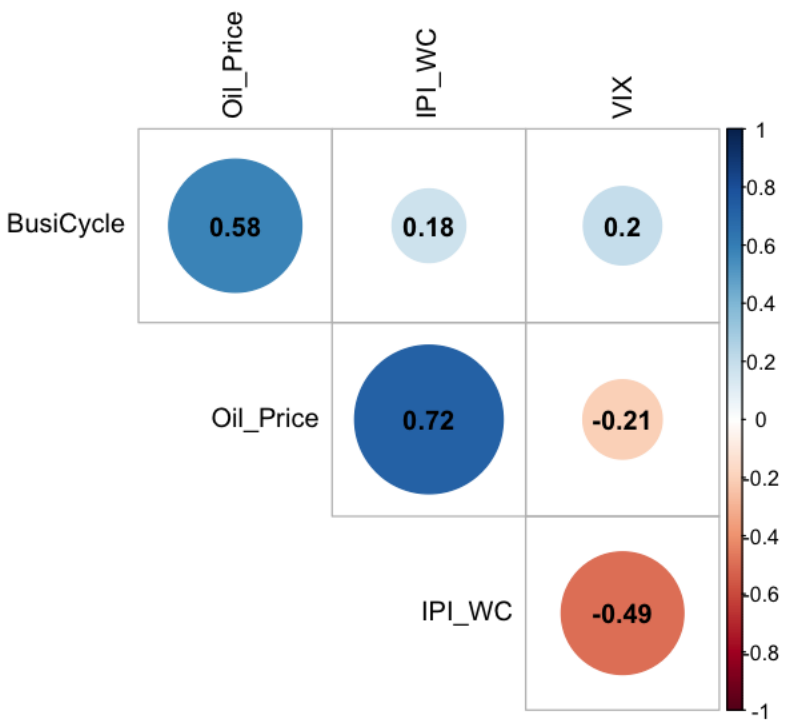
Figure 2-5: Correlation Plots of Quantitative Variables in Four Routes



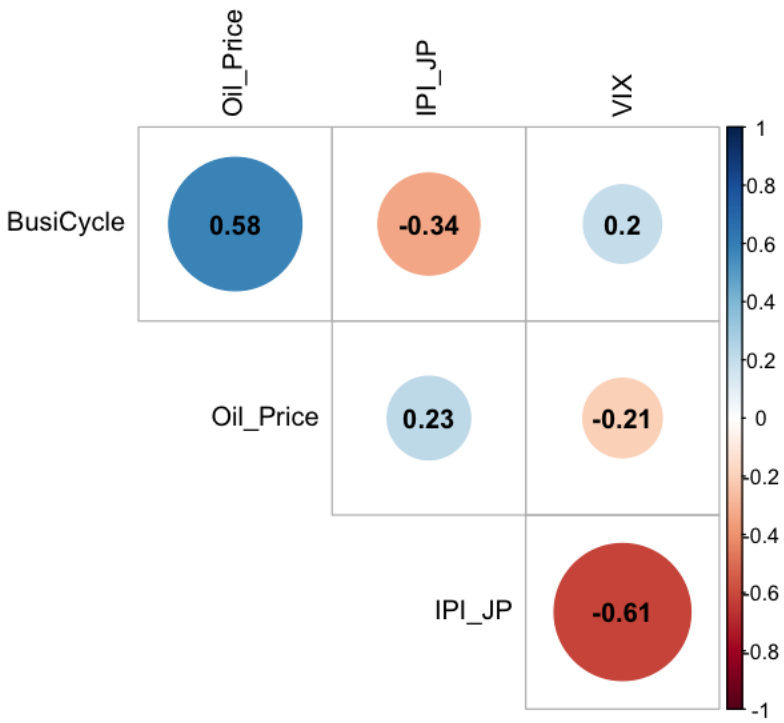
Route 1: Europe



Route 2: West Mediterranean



Route 3: West Coast of North America



Route 4: East Japan

Table 3: Regression Results of Europe Route (with different event horizon)

	Dependent variable:						
	China to Europe Freight Rates						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
one_week	-0.131						
	(0.289)						
one_month		-0.035					
		(0.144)					
two_month			0.001				
			(0.106)				
three_month				0.075			
				(0.096)			
four_month					0.121		
					(0.091)		
five_month						0.164*	
						(0.088)	
six_month							0.260***
							(0.085)
BusiCycle	1.240***	1.242***	1.239***	1.244***	1.259***	1.263***	1.269***
	(0.297)	(0.298)	(0.297)	(0.297)	(0.297)	(0.296)	(0.294)
Oil_Price	0.324***	0.324***	0.325***	0.338***	0.348***	0.363***	0.378***
	(0.124)	(0.125)	(0.125)	(0.126)	(0.125)	(0.126)	(0.124)
IPI_EU	1.132	1.136	1.150	0.971	0.749	0.542	0.226
	(1.213)	(1.215)	(1.217)	(1.234)	(1.248)	(1.250)	(1.235)
VIX	0.029	0.028	0.030	0.036	0.038	0.045	0.051
	(0.078)	(0.078)	(0.078)	(0.078)	(0.078)	(0.078)	(0.077)
Year_2015	-1.630***	-1.629***	-1.629***	-1.625***	-1.621***	-1.615***	-1.611***
	(0.186)	(0.186)	(0.186)	(0.186)	(0.185)	(0.185)	(0.183)
Year_2016	-1.459***	-1.458***	-1.459***	-1.449***	-1.439***	-1.427***	-1.416***
	(0.211)	(0.211)	(0.211)	(0.211)	(0.211)	(0.210)	(0.208)
Year_2017	-1.278***	-1.278***	-1.278***	-1.267***	-1.257***	-1.243***	-1.229***
	(0.191)	(0.191)	(0.191)	(0.191)	(0.191)	(0.191)	(0.189)
Year_2018	-1.615***	-1.615***	-1.616***	-1.610***	-1.605***	-1.597***	-1.589***
	(0.142)	(0.142)	(0.142)	(0.142)	(0.142)	(0.142)	(0.141)
Year_2019	-1.597***	-1.596***	-1.597***	-1.591***	-1.587***	-1.579***	-1.571***
	(0.150)	(0.150)	(0.150)	(0.150)	(0.150)	(0.150)	(0.149)
Year_2020	-1.108***	-1.108***	-1.108***	-1.107***	-1.106***	-1.103***	-1.103***
	(0.156)	(0.156)	(0.156)	(0.155)	(0.155)	(0.155)	(0.154)
Year_2021	0.075	0.076	0.072	0.055	0.036	0.014	-0.044

	(0.100)	(0.101)	(0.102)	(0.102)	(0.104)	(0.104)	(0.106)
Jan	0.212**	0.213**	0.212**	0.214**	0.218**	0.219**	0.221**
	(0.093)	(0.094)	(0.093)	(0.093)	(0.093)	(0.093)	(0.092)
Feb	0.184	0.185	0.184	0.185	0.189	0.190	0.190
	(0.121)	(0.121)	(0.121)	(0.121)	(0.121)	(0.120)	(0.119)
Mar	-0.191**	-0.190**	-0.191**	-0.192**	-0.190**	-0.191**	-0.194**
	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)	(0.094)	(0.094)
Apr	-0.298***	-0.296***	-0.302***	-0.313***	-0.319***	-0.325***	-0.341***
	(0.088)	(0.090)	(0.089)	(0.089)	(0.088)	(0.088)	(0.087)
May	-0.118	-0.118	-0.118	-0.130	-0.138	-0.146*	-0.164*
	(0.084)	(0.084)	(0.086)	(0.086)	(0.085)	(0.085)	(0.085)
Jun	-0.212***	-0.212***	-0.212***	-0.224***	-0.231***	-0.239***	-0.256***
	(0.081)	(0.081)	(0.081)	(0.082)	(0.082)	(0.081)	(0.081)
Jul	-0.038	-0.037	-0.037	-0.041	-0.059	-0.068	-0.086
	(0.078)	(0.078)	(0.078)	(0.078)	(0.080)	(0.079)	(0.079)
Aug	-0.028	-0.027	-0.027	-0.030	-0.032	-0.057	-0.076
	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)	(0.079)	(0.078)
Sep	-0.132*	-0.132*	-0.132*	-0.134*	-0.136*	-0.138*	-0.177**
	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)
Oct	-0.262***	-0.262***	-0.262***	-0.262***	-0.261***	-0.261***	-0.270***
	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)	(0.075)
Nov	-0.137*	-0.137*	-0.137*	-0.138*	-0.138*	-0.139*	-0.141*
	(0.073)	(0.073)	(0.073)	(0.073)	(0.073)	(0.072)	(0.072)
Constant	-4.682	-4.706	-4.764	-4.037	-3.127	-2.274	-0.914
	(5.490)	(5.493)	(5.499)	(5.562)	(5.613)	(5.622)	(5.561)
Observations	383	383	383	383	383	383	383
R^2	0.908	0.908	0.908	0.909	0.909	0.909	0.911
Adjusted R^2	0.903	0.903	0.903	0.903	0.903	0.903	0.905
Residual Std. Error (df = 359)	0.282	0.282	0.282	0.281	0.281	0.280	0.278
F Statistic (df = 23; 359)	154.916***	154.845***	154.817***	155.109***	155.652***	156.479***	159.286***
Note:							*p<0.1; **p<0.05; ***p<0.01

Table 4: Regression Results of the West Mediterranean Route (with different event horizon)

	Dependent variable:						
	China to the West Mediterranean Freight Rates						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
one_week	-0.147						
	(0.332)						
one_month		-0.048					
		(0.167)					
two_month			-0.007				
			(0.123)				
three_month				0.048			
				(0.109)			
four_month					0.086		
					(0.101)		
five_month						0.108	
						(0.098)	
six_month							0.174*
							(0.096)
BusiCycle	1.210***	1.212***	1.210***	1.212***	1.218***	1.216***	1.213***
	(0.341)	(0.341)	(0.341)	(0.341)	(0.341)	(0.340)	(0.339)
Oil_Price	0.680***	0.679***	0.683***	0.690***	0.688***	0.687***	0.678***
	(0.150)	(0.151)	(0.151)	(0.151)	(0.150)	(0.150)	(0.149)
IPI_WM	-1.349**	-1.345**	-1.363**	-1.384**	-1.373**	-1.347**	-1.285**
	(0.587)	(0.591)	(0.590)	(0.587)	(0.585)	(0.585)	(0.585)
VIX	0.097	0.097	0.098	0.102	0.104	0.109	0.114
	(0.089)	(0.090)	(0.090)	(0.090)	(0.090)	(0.090)	(0.089)
Year_2015	-1.309***	-1.308***	-1.308***	-1.303***	-1.298***	-1.295***	-1.294***
	(0.215)	(0.215)	(0.215)	(0.215)	(0.215)	(0.215)	(0.214)
Year_2016	-1.184***	-1.183***	-1.183***	-1.175***	-1.171***	-1.169***	-1.170***
	(0.248)	(0.248)	(0.248)	(0.248)	(0.248)	(0.248)	(0.247)
Year_2017	-1.111***	-1.111***	-1.110***	-1.102***	-1.098***	-1.094***	-1.093***
	(0.224)	(0.224)	(0.224)	(0.224)	(0.224)	(0.224)	(0.223)
Year_2018	-1.526***	-1.525***	-1.525***	-1.521***	-1.518***	-1.515***	-1.514***
	(0.166)	(0.166)	(0.167)	(0.167)	(0.166)	(0.166)	(0.166)
Year_2019	-1.336***	-1.335***	-1.335***	-1.330***	-1.327***	-1.324***	-1.324***
	(0.178)	(0.178)	(0.178)	(0.178)	(0.178)	(0.178)	(0.177)
Year_2020	-0.922***	-0.921***	-0.922***	-0.918***	-0.916***	-0.914***	-0.914***
	(0.180)	(0.180)	(0.180)	(0.180)	(0.180)	(0.180)	(0.179)
Year_2021	0.139	0.141	0.137	0.126	0.111	0.098	0.056

	(0.116)	(0.117)	(0.118)	(0.118)	(0.120)	(0.121)	(0.124)
Jan	0.288***	0.289***	0.288***	0.289***	0.290***	0.290***	0.288***
	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)	(0.106)
Feb	0.246*	0.247*	0.246*	0.246*	0.247*	0.246*	0.244*
	(0.138)	(0.139)	(0.138)	(0.138)	(0.138)	(0.138)	(0.138)
Mar	-0.081	-0.081	-0.082	-0.083	-0.082	-0.083	-0.085
	(0.109)	(0.109)	(0.109)	(0.109)	(0.109)	(0.109)	(0.109)
Apr	-0.159	-0.156	-0.163	-0.171*	-0.176*	-0.178*	-0.186*
	(0.102)	(0.105)	(0.103)	(0.103)	(0.102)	(0.102)	(0.102)
May	-0.054	-0.054	-0.054	-0.062	-0.066	-0.068	-0.076
	(0.097)	(0.097)	(0.099)	(0.098)	(0.098)	(0.098)	(0.097)
Jun	-0.133	-0.133	-0.133	-0.141	-0.145	-0.148	-0.156*
	(0.093)	(0.093)	(0.093)	(0.094)	(0.094)	(0.094)	(0.093)
Jul	-0.075	-0.074	-0.075	-0.076	-0.087	-0.090	-0.099
	(0.089)	(0.089)	(0.089)	(0.089)	(0.090)	(0.089)	(0.089)
Aug	-0.006	-0.006	-0.006	-0.006	-0.006	-0.021	-0.030
	(0.087)	(0.087)	(0.087)	(0.087)	(0.087)	(0.088)	(0.088)
Sep	-0.039	-0.039	-0.040	-0.040	-0.040	-0.040	-0.064
	(0.085)	(0.085)	(0.085)	(0.085)	(0.085)	(0.085)	(0.086)
Oct	-0.250***	-0.250***	-0.251***	-0.251***	-0.250***	-0.250***	-0.256***
	(0.088)	(0.088)	(0.088)	(0.088)	(0.088)	(0.088)	(0.087)
Nov	-0.138*	-0.138	-0.138*	-0.138*	-0.138*	-0.138*	-0.139*
	(0.084)	(0.084)	(0.084)	(0.084)	(0.083)	(0.083)	(0.083)
Constant	5.125*	5.100*	5.177*	5.226*	5.145*	5.021*	4.778
	(2.941)	(2.955)	(2.947)	(2.938)	(2.936)	(2.937)	(2.934)
Observations	383	383	383	383	383	383	383
R^2	0.874	0.874	0.874	0.874	0.874	0.874	0.875
Adjusted R^2	0.866	0.866	0.866	0.866	0.866	0.866	0.867
Residual Std. Error (df = 359)	0.323	0.323	0.323	0.323	0.323	0.323	0.322
F Statistic (df = 23; 359)	108.307***	108.267***	108.240***	108.307***	108.490***	108.662***	109.383***
Note:							*p<0.1; **p<0.05; ***p<0.01

Table 5: Regression Results of the West Coast of North America Route (with different event horizon)

	Dependent variable:						
	China to the West Coast of North America Freight Rates						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
one_week	-0.132						
	(0.236)						
one_month		-0.150					
		(0.118)					
two_month			-0.080				
			(0.088)				
three_month				-0.031			
				(0.078)			
four_month					0.004		
					(0.073)		
five_month						0.051	
						(0.070)	
six_month							0.074
							(0.069)
BusiCycle	1.134***	1.144***	1.133***	1.133***	1.134***	1.137***	1.136***
	(0.242)	(0.242)	(0.242)	(0.242)	(0.242)	(0.242)	(0.242)
Oil_Price	0.218*	0.206	0.203	0.213	0.221*	0.232*	0.235*
	(0.130)	(0.130)	(0.131)	(0.131)	(0.131)	(0.131)	(0.131)
IPI_WC	1.457	1.537	1.578	1.502	1.439	1.357	1.322
	(0.984)	(0.984)	(0.994)	(0.994)	(0.992)	(0.991)	(0.989)
VIX	0.103	0.097	0.099	0.102	0.105	0.110*	0.112*
	(0.064)	(0.064)	(0.064)	(0.064)	(0.064)	(0.064)	(0.064)
Year_2015	-1.061***	-1.061***	-1.070***	-1.066***	-1.060***	-1.051***	-1.048***
	(0.157)	(0.157)	(0.157)	(0.157)	(0.157)	(0.157)	(0.157)
Year_2016	-1.075***	-1.075***	-1.084***	-1.079***	-1.073***	-1.063***	-1.060***
	(0.176)	(0.175)	(0.176)	(0.176)	(0.176)	(0.176)	(0.176)
Year_2017	-1.019***	-1.020***	-1.028***	-1.023***	-1.017***	-1.007***	-1.004***
	(0.159)	(0.158)	(0.159)	(0.159)	(0.159)	(0.159)	(0.159)
Year_2018	-1.166***	-1.166***	-1.173***	-1.170***	-1.165***	-1.158***	-1.155***
	(0.122)	(0.121)	(0.122)	(0.122)	(0.122)	(0.122)	(0.122)
Year_2019	-1.190***	-1.190***	-1.198***	-1.194***	-1.189***	-1.180***	-1.178***
	(0.129)	(0.128)	(0.129)	(0.129)	(0.129)	(0.129)	(0.129)
Year_2020	-0.584***	-0.582***	-0.588***	-0.587***	-0.584***	-0.580***	-0.579***
	(0.127)	(0.127)	(0.127)	(0.127)	(0.127)	(0.127)	(0.127)

Year_2021	-0.261***	-0.248***	-0.250***	-0.257***	-0.264***	-0.281***	-0.296***
	(0.082)	(0.083)	(0.083)	(0.084)	(0.085)	(0.086)	(0.087)
Jan	0.203***	0.205***	0.202***	0.203***	0.203***	0.205***	0.204***
	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)
Feb	0.288***	0.292***	0.288***	0.288***	0.287***	0.287***	0.287***
	(0.099)	(0.098)	(0.098)	(0.099)	(0.099)	(0.099)	(0.098)
Mar	-0.018	-0.014	-0.017	-0.018	-0.018	-0.019	-0.021
	(0.078)	(0.078)	(0.078)	(0.078)	(0.078)	(0.078)	(0.078)
Apr	-0.004	0.017	0.005	-0.003	-0.008	-0.015	-0.019
	(0.072)	(0.074)	(0.073)	(0.073)	(0.073)	(0.073)	(0.073)
May	-0.008	-0.005	0.004	-0.003	-0.009	-0.016	-0.020
	(0.069)	(0.069)	(0.071)	(0.071)	(0.070)	(0.070)	(0.070)
Jun	-0.050	-0.049	-0.047	-0.046	-0.051	-0.058	-0.062
	(0.066)	(0.066)	(0.066)	(0.067)	(0.066)	(0.066)	(0.066)
Jul	0.046	0.046	0.045	0.047	0.046	0.039	0.035
	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)
Aug	0.125**	0.126**	0.125**	0.125**	0.125**	0.118*	0.115*
	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)	(0.063)	(0.063)
Sep	0.180***	0.182***	0.181***	0.181***	0.180***	0.180***	0.169***
	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)	(0.062)
Oct	0.212***	0.213***	0.212***	0.212***	0.212***	0.212***	0.209***
	(0.063)	(0.062)	(0.062)	(0.063)	(0.063)	(0.063)	(0.062)
Nov	0.136**	0.137**	0.136**	0.136**	0.136**	0.136**	0.136**
	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)
Constant	-5.551	-5.901	-6.024	-5.724	-5.485	-5.182	-5.033
	(4.310)	(4.312)	(4.343)	(4.345)	(4.335)	(4.331)	(4.327)
Observations	383	383	383	383	383	383	383
R^2	0.873	0.874	0.873	0.873	0.873	0.873	0.874
Adjusted R^2	0.865	0.866	0.865	0.865	0.865	0.865	0.865
Residual Std. Error (df = 359)	0.230	0.230	0.230	0.230	0.230	0.230	0.230
F Statistic (df = 23; 359)	107.565***	108.012***	107.741***	107.510***	107.458***	107.639***	107.853***
Note:							*p<0.1; **p<0.05; ***p<0.01

Table 6: Regression Results of East Japan Route (with different event horizon)

	Dependent variable:						
	China to East Japan Freight Rates						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
one_week	-0.131						
	(0.185)						
one_month		-0.257***					
		(0.091)					
two_month			-0.176**				
			(0.068)				
three_month				-0.173***			
				(0.062)			
four_month					-0.165***		
					(0.058)		
five_month						-0.187***	
						(0.055)	
six_month							-0.181***
							(0.052)
BusiCycle	0.780***	0.793***	0.770***	0.763***	0.750***	0.755***	0.774***
	(0.190)	(0.188)	(0.189)	(0.188)	(0.189)	(0.188)	(0.187)
Oil_Price	0.074	0.057	0.051	0.038	0.040	0.040	0.071
	(0.082)	(0.081)	(0.081)	(0.082)	(0.082)	(0.081)	(0.080)
IPI_JP	-0.654	-0.569	-0.508	-0.385	-0.353	-0.394	-0.672
	(0.435)	(0.430)	(0.434)	(0.441)	(0.444)	(0.434)	(0.426)
VIX	-0.005	-0.017	-0.017	-0.022	-0.018	-0.024	-0.019
	(0.050)	(0.049)	(0.050)	(0.050)	(0.049)	(0.049)	(0.049)
Year_2015	0.454***	0.447***	0.423***	0.399***	0.391***	0.392***	0.438***
	(0.136)	(0.134)	(0.135)	(0.136)	(0.136)	(0.135)	(0.134)
Year_2016	-0.216	-0.227	-0.253	-0.281*	-0.288*	-0.288*	-0.234
	(0.155)	(0.153)	(0.154)	(0.155)	(0.155)	(0.154)	(0.152)
Year_2017	0.007	-0.006	-0.031	-0.060	-0.066	-0.068	-0.013
	(0.144)	(0.143)	(0.144)	(0.145)	(0.145)	(0.144)	(0.142)
Year_2018	-0.206*	-0.213*	-0.235**	-0.259**	-0.266**	-0.265**	-0.220**
	(0.113)	(0.112)	(0.113)	(0.114)	(0.114)	(0.113)	(0.111)
Year_2019	-0.583***	-0.590***	-0.611***	-0.633***	-0.639***	-0.640***	-0.598***
	(0.113)	(0.112)	(0.113)	(0.113)	(0.114)	(0.113)	(0.111)
Year_2020	-0.698***	-0.698***	-0.714***	-0.726***	-0.729***	-0.731***	-0.709***
	(0.103)	(0.102)	(0.103)	(0.103)	(0.103)	(0.102)	(0.102)
Year_2021	-0.575***	-0.556***	-0.556***	-0.555***	-0.546***	-0.527***	-0.496***

	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.072)
Jan	0.097	0.099*	0.093	0.089	0.086	0.088	0.097
	(0.061)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)
Feb	0.091	0.096	0.087	0.083	0.079	0.082	0.092
	(0.078)	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)
Mar	0.022	0.026	0.020	0.018	0.015	0.018	0.025
	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)	(0.060)	(0.060)
Apr	0.043	0.079	0.063	0.061	0.058	0.062	0.064
	(0.056)	(0.057)	(0.056)	(0.056)	(0.056)	(0.055)	(0.055)
May	-0.119**	-0.116**	-0.095*	-0.094*	-0.095*	-0.092*	-0.095*
	(0.053)	(0.053)	(0.054)	(0.054)	(0.053)	(0.053)	(0.053)
Jun	-0.146***	-0.144***	-0.140***	-0.122**	-0.124**	-0.120**	-0.121**
	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)
Jul	-0.172***	-0.171***	-0.173***	-0.168***	-0.148***	-0.145***	-0.145***
	(0.049)	(0.048)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)
Aug	-0.211***	-0.210***	-0.211***	-0.212***	-0.212***	-0.186***	-0.186***
	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)
Sep	-0.124***	-0.122***	-0.123***	-0.122***	-0.123***	-0.122***	-0.098**
	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)
Oct	-0.030	-0.029	-0.031	-0.031	-0.032	-0.032	-0.025
	(0.049)	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)
Nov	0.010	0.010	0.009	0.009	0.009	0.009	0.011
	(0.047)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)
Constant	5.208***	4.856**	4.728**	4.288**	4.188**	4.370**	5.370***
	(1.958)	(1.938)	(1.948)	(1.966)	(1.971)	(1.941)	(1.921)
Observations	383	383	383	383	383	383	383
R^2	0.794	0.798	0.798	0.798	0.798	0.800	0.801
Adjusted R^2	0.781	0.785	0.785	0.785	0.786	0.788	0.788
Residual Std. Error (df = 359)	0.180	0.178	0.178	0.178	0.178	0.177	0.177
F Statistic (df = 23; 359)	60.235***	61.799***	61.539***	61.798***	61.832***	62.594***	62.643***
Note:							*p<0.1; **p<0.05; ***p<0.01

Table 7: Regression Results of Europe Route (monthly marginal effect)

	Dependent variable:							
	China to Europe Freight Rates							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
week_12	-0.093							
	(0.209)							
week_34		-0.024						
		(0.209)						
month_2			0.002					
			(0.153)					
month_3				0.177				
				(0.155)				
month_4					0.147			
					(0.155)			
month_5						0.167		
						(0.138)		
month_6							0.228	
							(0.140)	
month_7								0.386**
								(0.157)
BusiCycle	1.241***	1.240***	1.239***	1.246***	1.254***	1.242***	1.232***	1.231***
	(0.297)	(0.297)	(0.297)	(0.297)	(0.297)	(0.297)	(0.296)	(0.295)
Oil_Price	0.323***	0.324***	0.324***	0.340***	0.333***	0.329***	0.327***	0.290**
	(0.125)	(0.125)	(0.125)	(0.125)	(0.125)	(0.124)	(0.124)	(0.124)
IPI_EU	1.130	1.147	1.150	0.912	0.931	1.067	1.099	1.498
	(1.214)	(1.213)	(1.216)	(1.229)	(1.234)	(1.213)	(1.209)	(1.211)
VIX	0.028	0.030	0.030	0.034	0.031	0.032	0.032	0.029
	(0.078)	(0.078)	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)
Year_2015	-1.630***	-1.629***	-1.629***	-1.624***	-1.626***	-1.626***	-1.631***	-1.634***
	(0.186)	(0.186)	(0.186)	(0.185)	(0.185)	(0.185)	(0.185)	(0.184)
Year_2016	-1.460***	-1.459***	-1.459***	-1.447***	-1.450***	-1.454***	-1.459***	-1.477***
	(0.211)	(0.211)	(0.211)	(0.211)	(0.211)	(0.210)	(0.210)	(0.209)
Year_2017	-1.279***	-1.278***	-1.278***	-1.265***	-1.269***	-1.273***	-1.277***	-1.292***
	(0.191)	(0.191)	(0.191)	(0.191)	(0.191)	(0.190)	(0.190)	(0.189)
Year_2018	-1.616***	-1.615***	-1.616***	-1.609***	-1.610***	-1.612***	-1.615***	-1.621***
	(0.142)	(0.142)	(0.142)	(0.142)	(0.142)	(0.142)	(0.142)	(0.141)
Year_2019	-1.597***	-1.597***	-1.597***	-1.590***	-1.592***	-1.593***	-1.596***	-1.602***
	(0.150)	(0.150)	(0.150)	(0.150)	(0.150)	(0.150)	(0.150)	(0.149)
Year_2020	-1.109***	-1.108***	-1.108***	-1.106***	-1.108***	-1.107***	-1.110***	-1.116***

	(0.156)	(0.156)	(0.156)	(0.155)	(0.155)	(0.155)	(0.155)	(0.154)
Year_2021	0.076	0.073	0.072	0.063	0.063	0.059	0.053	0.040
	(0.101)	(0.101)	(0.101)	(0.100)	(0.101)	(0.101)	(0.101)	(0.100)
Jan	0.213**	0.212**	0.212**	0.215**	0.216**	0.213**	0.211**	0.207**
	(0.093)	(0.094)	(0.094)	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)
Feb	0.185	0.184	0.184	0.186	0.189	0.185	0.181	0.179
	(0.121)	(0.121)	(0.121)	(0.121)	(0.121)	(0.121)	(0.121)	(0.120)
Mar	-0.190**	-0.191**	-0.191**	-0.191**	-0.189**	-0.191**	-0.194**	-0.194**
	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)	(0.094)
Apr	-0.296***	-0.300***	-0.302***	-0.302***	-0.301***	-0.302***	-0.303***	-0.303***
	(0.088)	(0.089)	(0.088)	(0.087)	(0.087)	(0.087)	(0.087)	(0.087)
May	-0.118	-0.118	-0.118	-0.127	-0.120	-0.119	-0.120	-0.116
	(0.084)	(0.084)	(0.086)	(0.085)	(0.084)	(0.084)	(0.084)	(0.084)
Jun	-0.212***	-0.212***	-0.212***	-0.232***	-0.218***	-0.213***	-0.214***	-0.211***
	(0.081)	(0.081)	(0.081)	(0.082)	(0.081)	(0.080)	(0.080)	(0.080)
Jul	-0.038	-0.037	-0.037	-0.040	-0.053	-0.048	-0.039	-0.033
	(0.078)	(0.078)	(0.078)	(0.078)	(0.080)	(0.079)	(0.078)	(0.078)
Aug	-0.028	-0.027	-0.027	-0.030	-0.030	-0.045	-0.037	-0.024
	(0.077)	(0.077)	(0.077)	(0.077)	(0.077)	(0.079)	(0.077)	(0.077)
Sep	-0.132*	-0.132*	-0.132*	-0.134*	-0.134*	-0.133*	-0.164**	-0.131*
	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.077)	(0.074)
Oct	-0.262***	-0.262***	-0.262***	-0.262***	-0.261***	-0.262***	-0.263***	-0.312***
	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)	(0.078)
Nov	-0.137*	-0.137*	-0.137*	-0.138*	-0.138*	-0.138*	-0.138*	-0.138*
	(0.073)	(0.073)	(0.073)	(0.073)	(0.073)	(0.073)	(0.073)	(0.072)
Constant	-4.671	-4.753	-4.763	-3.773	-3.862	-4.417	-4.499	-6.182
	(5.491)	(5.489)	(5.499)	(5.546)	(5.564)	(5.485)	(5.470)	(5.473)
Observations	383	383	383	383	383	383	383	383
R^2	0.908	0.908	0.908	0.909	0.909	0.909	0.909	0.910
Adjusted R^2	0.903	0.903	0.903	0.903	0.903	0.903	0.903	0.904
Residual Std. Error (df = 359)	0.282	0.282	0.282	0.281	0.281	0.281	0.281	0.279
F Statistic (df = 23; 359)	154.910***	154.823***	154.817***	155.440***	155.245***	155.514***	156.076***	157.697***
Note:								*p<0.1; **p<0.05; ***p<0.01

Table 8: Regression Results of the West Mediterranean Route (monthly marginal effect)

	Dependent variable:							
	China to the West Mediterranean Freight Rates							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
week_12	-0.109							
	(0.241)							
week_34		-0.014						
		(0.241)						
month_2			-0.001					
			(0.175)					
month_3				0.126				
				(0.175)				
month_4					0.124			
					(0.175)			
month_5						0.118		
						(0.159)		
month_6							0.143	
							(0.162)	
month_7								0.362**
								(0.180)
BusiCycle	1.211***	1.210***	1.210***	1.211***	1.217***	1.209***	1.203***	1.205***
	(0.341)	(0.341)	(0.341)	(0.341)	(0.341)	(0.340)	(0.340)	(0.339)
Oil_Price	0.678***	0.684***	0.684***	0.686***	0.677***	0.679***	0.679***	0.651***
	(0.151)	(0.150)	(0.150)	(0.150)	(0.150)	(0.150)	(0.150)	(0.150)
IPI_WM	-1.340**	-1.364**	-1.367**	-1.357**	-1.327**	-1.328**	-1.329**	-1.244**
	(0.588)	(0.587)	(0.586)	(0.585)	(0.588)	(0.587)	(0.587)	(0.586)
VIX	0.096	0.098	0.098	0.102	0.100	0.100	0.100	0.099
	(0.090)	(0.090)	(0.089)	(0.089)	(0.089)	(0.089)	(0.089)	(0.089)
Year_2015	-1.309***	-1.308***	-1.308***	-1.303***	-1.305***	-1.307***	-1.310***	-1.322***
	(0.215)	(0.215)	(0.215)	(0.215)	(0.215)	(0.215)	(0.215)	(0.214)
Year_2016	-1.185***	-1.182***	-1.182***	-1.177***	-1.181***	-1.183***	-1.186***	-1.206***
	(0.248)	(0.248)	(0.248)	(0.248)	(0.248)	(0.248)	(0.248)	(0.247)
Year_2017	-1.113***	-1.109***	-1.109***	-1.104***	-1.108***	-1.109***	-1.112***	-1.128***
	(0.224)	(0.224)	(0.224)	(0.224)	(0.224)	(0.224)	(0.224)	(0.223)
Year_2018	-1.526***	-1.525***	-1.525***	-1.521***	-1.523***	-1.524***	-1.526***	-1.535***
	(0.166)	(0.166)	(0.167)	(0.166)	(0.166)	(0.166)	(0.166)	(0.166)
Year_2019	-1.337***	-1.335***	-1.335***	-1.331***	-1.334***	-1.335***	-1.337***	-1.349***
	(0.178)	(0.178)	(0.178)	(0.178)	(0.178)	(0.178)	(0.178)	(0.177)
Year_2020	-0.923***	-0.921***	-0.922***	-0.918***	-0.921***	-0.921***	-0.924***	-0.938***

	(0.180)	(0.180)	(0.180)	(0.180)	(0.180)	(0.180)	(0.180)	(0.179)
Year_2021	0.140	0.137	0.136	0.130	0.127	0.126	0.123	0.103
	(0.116)	(0.116)	(0.117)	(0.116)	(0.117)	(0.117)	(0.117)	(0.117)
Jan	0.289***	0.289***	0.288***	0.289***	0.290***	0.288***	0.287***	0.286***
	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)	(0.106)
Feb	0.247*	0.246*	0.246*	0.246*	0.248*	0.246*	0.244*	0.244*
	(0.138)	(0.139)	(0.139)	(0.138)	(0.138)	(0.138)	(0.138)	(0.138)
Mar	-0.081	-0.082	-0.082	-0.082	-0.080	-0.082	-0.083	-0.082
	(0.109)	(0.109)	(0.109)	(0.109)	(0.109)	(0.109)	(0.109)	(0.109)
Apr	-0.157	-0.163	-0.164	-0.163	-0.162	-0.163	-0.164	-0.163
	(0.103)	(0.103)	(0.102)	(0.101)	(0.102)	(0.101)	(0.101)	(0.101)
May	-0.054	-0.055	-0.055	-0.059	-0.053	-0.054	-0.055	-0.053
	(0.097)	(0.097)	(0.099)	(0.097)	(0.097)	(0.097)	(0.097)	(0.096)
Jun	-0.133	-0.134	-0.134	-0.146	-0.136	-0.133	-0.134	-0.132
	(0.093)	(0.093)	(0.093)	(0.094)	(0.093)	(0.093)	(0.093)	(0.092)
Jul	-0.074	-0.075	-0.075	-0.074	-0.085	-0.081	-0.075	-0.073
	(0.089)	(0.089)	(0.089)	(0.089)	(0.090)	(0.089)	(0.089)	(0.088)
Aug	-0.006	-0.006	-0.006	-0.006	-0.006	-0.018	-0.012	-0.007
	(0.087)	(0.087)	(0.087)	(0.087)	(0.087)	(0.088)	(0.087)	(0.087)
Sep	-0.039	-0.040	-0.040	-0.040	-0.039	-0.040	-0.059	-0.040
	(0.085)	(0.085)	(0.085)	(0.085)	(0.085)	(0.085)	(0.088)	(0.085)
Oct	-0.250***	-0.251***	-0.251***	-0.251***	-0.250***	-0.250***	-0.251***	-0.297***
	(0.088)	(0.088)	(0.088)	(0.088)	(0.088)	(0.088)	(0.088)	(0.090)
Nov	-0.138*	-0.138	-0.138*	-0.138*	-0.138*	-0.138*	-0.138*	-0.139*
	(0.084)	(0.084)	(0.084)	(0.083)	(0.083)	(0.083)	(0.083)	(0.083)
Constant	5.094*	5.180*	5.190*	5.124*	4.997*	5.032*	5.071*	4.794
	(2.945)	(2.943)	(2.939)	(2.938)	(2.949)	(2.944)	(2.938)	(2.929)
Observations	383	383	383	383	383	383	383	383
R^2	0.874	0.874	0.874	0.874	0.874	0.874	0.874	0.875
Adjusted R^2	0.866	0.866	0.866	0.866	0.866	0.866	0.866	0.867
Residual Std. Error (df = 359)	0.323	0.323	0.323	0.323	0.323	0.323	0.323	0.322
F Statistic (df = 23; 359)	108.309***	108.240***	108.239***	108.418***	108.413***	108.429***	108.507***	109.628***
Note:								*p<0.1; **p<0.05; ***p<0.01

Table 9: Regression Results of the West Coast of North America Route (monthly marginal effect)

	Dependent variable:							
	China to the West Coast of North America Freight Rates							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
week_12	-0.138							
	(0.171)							
week_34		-0.149						
		(0.171)						
month_2			-0.041					
			(0.125)					
month_3				0.069				
				(0.125)				
month_4					0.079			
					(0.124)			
month_5						0.125		
						(0.113)		
month_6							0.112	
							(0.115)	
month_7								0.049
								(0.128)
BusiCycle	1.136***	1.139***	1.131***	1.134***	1.139***	1.134***	1.129***	1.133***
	(0.242)	(0.242)	(0.242)	(0.242)	(0.242)	(0.242)	(0.242)	(0.242)
Oil_Price	0.214	0.214	0.217*	0.225*	0.219*	0.221*	0.219*	0.218*
	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)
IPI_WC	1.481	1.483	1.478	1.411	1.452	1.437	1.461	1.447
	(0.984)	(0.984)	(0.989)	(0.986)	(0.984)	(0.982)	(0.983)	(0.984)
VIX	0.101	0.101	0.105	0.107*	0.105*	0.106*	0.105*	0.105
	(0.064)	(0.064)	(0.064)	(0.064)	(0.064)	(0.064)	(0.064)	(0.064)
Year_2015	-1.063***	-1.060***	-1.063***	-1.056***	-1.058***	-1.057***	-1.062***	-1.062***
	(0.157)	(0.157)	(0.157)	(0.157)	(0.157)	(0.157)	(0.157)	(0.157)
Year_2016	-1.076***	-1.074***	-1.076***	-1.069***	-1.071***	-1.070***	-1.075***	-1.075***
	(0.176)	(0.176)	(0.176)	(0.176)	(0.176)	(0.176)	(0.176)	(0.176)
Year_2017	-1.021***	-1.019***	-1.020***	-1.013***	-1.015***	-1.014***	-1.018***	-1.019***
	(0.159)	(0.158)	(0.159)	(0.159)	(0.159)	(0.158)	(0.158)	(0.159)
Year_2018	-1.167***	-1.166***	-1.168***	-1.162***	-1.164***	-1.163***	-1.166***	-1.166***
	(0.122)	(0.122)	(0.122)	(0.122)	(0.122)	(0.121)	(0.121)	(0.122)
Year_2019	-1.191***	-1.190***	-1.192***	-1.186***	-1.187***	-1.186***	-1.190***	-1.190***
	(0.129)	(0.129)	(0.129)	(0.129)	(0.129)	(0.128)	(0.128)	(0.129)

Year_2020	-0.585***	-0.583***	-0.586***	-0.582***	-0.583***	-0.582***	-0.585***	-0.586***
	(0.127)	(0.127)	(0.127)	(0.127)	(0.127)	(0.127)	(0.127)	(0.127)
Year_2021	-0.258***	-0.257***	-0.260***	-0.266***	-0.268***	-0.273***	-0.273***	-0.267***
	(0.082)	(0.082)	(0.082)	(0.082)	(0.082)	(0.082)	(0.083)	(0.083)
Jan	0.204***	0.204***	0.203***	0.204***	0.204***	0.204***	0.202***	0.203***
	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)
Feb	0.289***	0.290***	0.287***	0.287***	0.289***	0.287***	0.286***	0.287***
	(0.098)	(0.099)	(0.099)	(0.099)	(0.099)	(0.098)	(0.098)	(0.099)
Mar	-0.017	-0.016	-0.019	-0.019	-0.017	-0.019	-0.020	-0.019
	(0.078)	(0.078)	(0.078)	(0.078)	(0.078)	(0.078)	(0.078)	(0.078)
Apr	0.001	0.002	-0.007	-0.008	-0.007	-0.008	-0.008	-0.008
	(0.073)	(0.073)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)
May	-0.007	-0.007	-0.004	-0.011	-0.007	-0.008	-0.009	-0.008
	(0.069)	(0.069)	(0.071)	(0.070)	(0.069)	(0.069)	(0.069)	(0.069)
Jun	-0.050	-0.050	-0.050	-0.058	-0.053	-0.051	-0.051	-0.051
	(0.066)	(0.066)	(0.066)	(0.067)	(0.066)	(0.066)	(0.066)	(0.066)
Jul	0.046	0.046	0.046	0.046	0.039	0.038	0.046	0.046
	(0.063)	(0.063)	(0.063)	(0.063)	(0.064)	(0.063)	(0.063)	(0.063)
Aug	0.125**	0.125**	0.125**	0.125**	0.125**	0.112*	0.121*	0.125**
	(0.062)	(0.062)	(0.062)	(0.062)	(0.062)	(0.063)	(0.062)	(0.062)
Sep	0.181***	0.181***	0.180***	0.180***	0.180***	0.180***	0.165***	0.180***
	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)	(0.063)	(0.061)
Oct	0.212***	0.212***	0.212***	0.212***	0.212***	0.212***	0.211***	0.205***
	(0.062)	(0.062)	(0.063)	(0.063)	(0.063)	(0.062)	(0.062)	(0.065)
Nov	0.136**	0.136**	0.136**	0.136**	0.136**	0.136**	0.136**	0.136**
	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)
Constant	-5.649	-5.674	-5.633	-5.378	-5.560	-5.484	-5.554	-5.502
	(4.310)	(4.310)	(4.327)	(4.315)	(4.309)	(4.303)	(4.305)	(4.310)
Observations	383	383	383	383	383	383	383	383
R^2	0.873	0.873	0.873	0.873	0.873	0.874	0.874	0.873
Adjusted R^2	0.865	0.865	0.865	0.865	0.865	0.866	0.865	0.865
Residual Std. Error (df = 359)	0.230	0.230	0.230	0.230	0.230	0.230	0.230	0.230
F Statistic (df = 23; 359)	107.681***	107.717***	107.493***	107.561***	107.596***	107.880***	107.783***	107.507***
Note:								*p<0.1; **p<0.05; ***p<0.01

Table 10: Regression Results of East Japan Route (monthly marginal effect)

	Dependent variable:							
	China to East Japan Freight Rates							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
week_12	-0.189							
	(0.135)							
week_34		-0.243*						
		(0.133)						
month_2			-0.091					
			(0.097)					
month_3				-0.092				
				(0.100)				
month_4					-0.020			
					(0.098)			
month_5						-0.072		
						(0.088)		
month_6							-0.148	
							(0.094)	
month_7								0.274***
								(0.101)
BusiCycle	0.781***	0.788***	0.775***	0.776***	0.779***	0.780***	0.796***	0.770***
	(0.190)	(0.190)	(0.190)	(0.190)	(0.191)	(0.190)	(0.190)	(0.189)
Oil_Price	0.066	0.072	0.078	0.069	0.077	0.079	0.099	0.045
	(0.082)	(0.081)	(0.081)	(0.082)	(0.081)	(0.081)	(0.082)	(0.082)
IPI_JP	-0.605	-0.661	-0.684	-0.607	-0.675	-0.694	-0.901**	-0.464
	(0.435)	(0.431)	(0.432)	(0.441)	(0.436)	(0.432)	(0.452)	(0.436)
VIX	-0.009	-0.009	-0.004	-0.007	-0.004	-0.004	-0.003	-0.007
	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.049)
Year_2015	0.446***	0.458***	0.456***	0.443***	0.457***	0.459***	0.492***	0.419***
	(0.136)	(0.135)	(0.136)	(0.137)	(0.136)	(0.136)	(0.137)	(0.135)
Year_2016	-0.226	-0.212	-0.213	-0.228	-0.213	-0.210	-0.171	-0.258*
	(0.155)	(0.154)	(0.154)	(0.156)	(0.155)	(0.154)	(0.156)	(0.154)
Year_2017	-0.003	0.010	0.011	-0.005	0.011	0.013	0.052	-0.033
	(0.144)	(0.143)	(0.144)	(0.145)	(0.145)	(0.144)	(0.146)	(0.144)
Year_2018	-0.214*	-0.203*	-0.204*	-0.217*	-0.204*	-0.202*	-0.169	-0.238**
	(0.113)	(0.112)	(0.113)	(0.114)	(0.113)	(0.113)	(0.114)	(0.113)
Year_2019	-0.591***	-0.580***	-0.581***	-0.593***	-0.581***	-0.580***	-0.550***	-0.613***
	(0.113)	(0.113)	(0.113)	(0.114)	(0.113)	(0.113)	(0.114)	(0.113)
Year_2020	-0.702***	-0.695***	-0.698***	-0.705***	-0.698***	-0.697***	-0.682***	-0.720***

	(0.103)	(0.103)	(0.103)	(0.104)	(0.103)	(0.103)	(0.103)	(0.103)
Year_2021	-0.574***	-0.567***	-0.570***	-0.576***	-0.575***	-0.570***	-0.551***	-0.612***
	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.071)	(0.070)
Jan	0.096	0.099	0.097	0.095	0.097	0.098	0.105*	0.090
	(0.060)	(0.060)	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)	(0.060)
Feb	0.091	0.094	0.090	0.089	0.090	0.091	0.099	0.084
	(0.078)	(0.078)	(0.078)	(0.078)	(0.078)	(0.078)	(0.078)	(0.077)
Mar	0.022	0.024	0.021	0.020	0.021	0.022	0.028	0.016
	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)
Apr	0.050	0.054	0.041	0.038	0.039	0.039	0.041	0.036
	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.055)
May	-0.118**	-0.118**	-0.111**	-0.116**	-0.120**	-0.120**	-0.121**	-0.118**
	(0.053)	(0.053)	(0.054)	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)
Jun	-0.146***	-0.145***	-0.147***	-0.137***	-0.146***	-0.147***	-0.146***	-0.146***
	(0.051)	(0.051)	(0.051)	(0.052)	(0.051)	(0.051)	(0.051)	(0.051)
Jul	-0.172***	-0.171***	-0.172***	-0.172***	-0.170***	-0.167***	-0.171***	-0.172***
	(0.049)	(0.049)	(0.049)	(0.049)	(0.050)	(0.049)	(0.049)	(0.049)
Aug	-0.211***	-0.210***	-0.211***	-0.211***	-0.211***	-0.203***	-0.205***	-0.212***
	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)	(0.049)	(0.048)	(0.048)
Sep	-0.123***	-0.123***	-0.124***	-0.124***	-0.124***	-0.124***	-0.104**	-0.124***
	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.049)	(0.047)
Oct	-0.030	-0.030	-0.031	-0.031	-0.031	-0.030	-0.029	-0.066
	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.050)
Nov	0.009	0.010	0.010	0.009	0.010	0.010	0.011	0.008
	(0.046)	(0.046)	(0.047)	(0.047)	(0.047)	(0.047)	(0.046)	(0.046)
Constant	5.027**	5.211***	5.340***	5.044**	5.291***	5.361***	6.118***	4.539**
	(1.958)	(1.944)	(1.950)	(1.973)	(1.958)	(1.951)	(2.010)	(1.954)
Observations	383	383	383	383	383	383	383	383
R^2	0.795	0.796	0.794	0.794	0.794	0.794	0.795	0.798
Adjusted R^2	0.782	0.783	0.781	0.781	0.781	0.781	0.782	0.785
Residual Std. Error (df = 359)	0.180	0.179	0.180	0.180	0.180	0.180	0.179	0.178
F Statistic (df = 23; 359)	60.544***	60.829***	60.315***	60.307***	60.138***	60.271***	60.652***	61.675***
Note:								*p<0.1; **p<0.05; ***p<0.01

Table 11: Regression Results with Single Event Regressor per Route

	Dependent variable:			
	Freight Rates to Each Route			
	EU	WM	WC	JP
	(1)	(2)	(3)	(4)
week_12	0.098	0.026	-0.095	-0.284**
	(0.212)	(0.247)	(0.177)	(0.137)
week_34	0.162	0.115	-0.105	-0.328**
	(0.212)	(0.247)	(0.177)	(0.136)
month_2	0.206	0.141	0.009	-0.169*
	(0.158)	(0.183)	(0.132)	(0.100)
month_3	0.379**	0.272	0.115	-0.170*
	(0.162)	(0.184)	(0.132)	(0.102)
month_4	0.363**	0.284	0.132	-0.105
	(0.162)	(0.185)	(0.131)	(0.101)
month_5	0.365**	0.272	0.170	-0.143
	(0.145)	(0.169)	(0.120)	(0.092)
month_6	0.409***	0.287*	0.154	-0.185*
	(0.146)	(0.170)	(0.121)	(0.097)
month_7	0.530***	0.488**	0.094	0.182*
	(0.160)	(0.188)	(0.134)	(0.105)
BusiCycle	1.279***	1.210***	1.145***	0.776***
	(0.292)	(0.340)	(0.243)	(0.188)
Oil_Price	0.354***	0.612***	0.212	0.034
	(0.124)	(0.152)	(0.132)	(0.083)
IPI_EU	0.220			
	(1.260)			
IPI_WM		-0.976		
		(0.601)		
IPI_WC			1.455	
			(0.999)	
IPI_JP				-0.465
				(0.470)
VIX	0.052	0.120	0.107*	-0.028
	(0.077)	(0.090)	(0.065)	(0.049)
Year_2015	-1.608***	-1.308***	-1.049***	0.406***
	(0.182)	(0.214)	(0.158)	(0.138)
Year_2016	-1.417***	-1.203***	-1.063***	-0.274*
	(0.208)	(0.248)	(0.177)	(0.157)
Year_2017	-1.225***	-1.119***	-1.005***	-0.054

	(0.188)	(0.223)	(0.160)	(0.147)
Year_2018	-1.580***	-1.524***	-1.153***	-0.250**
	(0.140)	(0.166)	(0.123)	(0.116)
Year_2019	-1.565***	-1.342***	-1.177***	-0.627***
	(0.148)	(0.178)	(0.130)	(0.115)
Year_2020	-1.109***	-0.934***	-0.577***	-0.726***
	(0.153)	(0.179)	(0.128)	(0.103)
Year_2021	-0.100	-0.006	-0.304***	-0.526***
	(0.107)	(0.126)	(0.089)	(0.075)
Jan	0.221**	0.285***	0.205***	0.093
	(0.092)	(0.106)	(0.076)	(0.060)
Feb	0.191	0.245*	0.290***	0.089
	(0.119)	(0.138)	(0.099)	(0.077)
Mar	-0.195**	-0.080	-0.018	0.023
	(0.093)	(0.109)	(0.078)	(0.060)
Apr	-0.325***	-0.166	0.005	0.078
	(0.088)	(0.104)	(0.074)	(0.056)
May	-0.165*	-0.068	-0.013	-0.094*
	(0.085)	(0.099)	(0.071)	(0.054)
Jun	-0.273***	-0.163*	-0.066	-0.123**
	(0.082)	(0.094)	(0.068)	(0.052)
Jul	-0.102	-0.109	0.024	-0.155***
	(0.080)	(0.090)	(0.064)	(0.049)
Aug	-0.093	-0.044	0.102	-0.190***
	(0.078)	(0.089)	(0.064)	(0.049)
Sep	-0.198***	-0.079	0.159**	-0.097**
	(0.076)	(0.088)	(0.063)	(0.048)
Oct	-0.329***	-0.311***	0.201***	-0.054
	(0.078)	(0.091)	(0.065)	(0.050)
Nov	-0.143**	-0.141*	0.135**	0.009
	(0.071)	(0.083)	(0.060)	(0.046)
Constant	-0.834	3.633	-5.582	4.613**
	(5.649)	(2.981)	(4.366)	(2.051)
Observations	383	383	383	383
R^2	0.914	0.878	0.875	0.805
Adjusted R^2	0.906	0.867	0.864	0.789
Residual Std. Error (df = 352)	0.276	0.322	0.231	0.177
F Statistic (df = 30; 352)	124.271***	84.136***	82.187***	48.558***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 12: Regression Results with Aggregated Data

	Dependent variable:
	Aggregated Freight Rates
week_12:effect	0.473*
	(0.278)
week_34:effect	0.598**
	(0.277)
month_2:effect	0.715***
	(0.200)
month_3:effect	0.925***
	(0.200)
month_4:effect	1.037***
	(0.199)
month_5:effect	1.072***
	(0.180)
month_6:effect	1.022***
	(0.181)
month_7:effect	1.119***
	(0.201)
BusiCycle	0.910***
	(0.283)
Oil_Price	-0.369***
	(0.114)
IPI	7.008***
	(0.463)
VIX	0.094
	(0.074)
Year_2015	-1.288***
	(0.179)
Year_2016	-1.561***
	(0.204)
Year_2017	-1.394***
	(0.185)
Year_2018	-1.554***
	(0.139)
Year_2019	-1.603***
	(0.147)
Year_2020	-1.027***
	(0.149)
Year_2021	-0.563***

	(0.098)
Jan	0.106
	(0.089)
Feb	0.127
	(0.115)
Mar	-0.077
	(0.090)
Apr	-0.085
	(0.085)
May	0.0003
	(0.080)
Jun	-0.126
	(0.077)
Jul	-0.081
	(0.074)
Aug	-0.076
	(0.073)
Sep	-0.069
	(0.072)
Oct	-0.148**
	(0.074)
Nov	-0.046
	(0.069)
Constant	-27.673***
	(2.431)
Observations	1,532
R^2	0.591
Adjusted R^2	0.583
Residual Std. Error	0.538 (df = 1501)
F Statistic	72.426*** (df = 30; 1501)
Note:	*p<0.1; **p<0.05; ***p<0.01

References

1. BBC News. (2021, March 24). Egypt's Suez Canal blocked by huge container ship. https://www.bbc.com/news/world-middle-east-56505413.
2. Beenstock, M., and Andreas, V. (1989). An econometric model of the world market for dry cargo freight and shipping." Applied Economics 21 (3):339-356. https://doi.org/10.1080/758522551.
3. Bildirici, M et al. (2016). BDI, Gold Price and Economic Growth. Procedia Economics and Finance 38: 280-286. https://doi.org/10.1016/S2212-5671(16)30200-3.
4. Chellel, K., Campbell, M. and Ha, K. (2021). Six Days in Suez: The Inside Story of the Ship That Broke Global Trade. Bloomberg.com. https://www.bloomberg.com/news/features/2021-06-24/how-the-billion-dollar-ever-given-cargo-ship-got-stuck-in-the-suez-canal.
5. Chen, P. (2015). Global oil prices, macroeconomic fundamentals and China's commodity sector comovements. Energy Policy 87: 284-294. https://doi.org/10.1016/j.enpol.2015.09.024.
6. China National Maritime Day Activity Organizing Committee. (2022). China National Maritime Day Announcement 2022. https://www.xindemarinenews.com/m/view.php?aid=40010.
7. Drobetz, W., Richter, T., and Wambach, M. (2012). Dynamics of time-varying volatility in the dry bulk and tanker freight markets. Applied Financial Economics 22 (16): 1367-1384. https://doi.org/10.1080/09603107.2012.657349.
8. Duerr, G. (2021, March 30). Suez Canal Blockage: Ship Freed, Heavy Traffic, International Impact. Digital Commons at Cedarville University. https://digitalcommons.cedarville.edu/history_and_government_media_contributions/1231/.
9. Erdogan, O., Tata, K., and Karahasan B. (2013). Dynamics of the co-movement between stock and maritime markets. International Review of Economics & Finance 25: 282 -290. https://doi.org/10.1016/j.iref.2012.07.007.
10. Feng, C et al. (2014). Log-transformation and its implications for data analysis. Shanghai Arch Psychiatry (2): 105-9. doi: 10.3969/j.issn.1002-0829.2014.02.009. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4120293/.
11. Gao, T., and Lu, J. (2019). The impacts of strait and canal blockages on the transportation costs of the Chinese fleet in the shipping network. Maritime Policy & Management, 46(6), 669–686. https://doi.org/10.1080/03088839.2019.1594423.
12. Georgiev, N. (2019). Bulk Shipping: Mass Shipping And Shipping Large Quantities. https://www.bluecart.com/blog/bulk-shipping.
13. Kelly, J. (2022). There Is A Massive Trucker Shortage Causing Supply Chain Disruptions And High Inflation. Forbes. https://www.forbes.com/sites/jackkelly/2022/01/12/there-is-a-massive-trucker-shortage-causing-supply-chain-disruptions-and-high-inflation/?sh=4db23425ec44.

14. Kickham, V. (2021, April 1). Supply chains brace for ripple effects of Suez Canal blockage. DC Velocity. https://www.dcvelocity.com/articles/50093-supply-chains-brace-for-ripple-effects-of-suez-canal-blockage.
15. Kim, H. (2011). Study about How the Chinese Economic Status Affects to the Baltic Dry Index. International Journal of Business and Management 6(3): 116-123. https://www.researchgate.net/publication/50315289_Study_about_How_the_Chinese_Economic_Status_Affects_to_the_Baltic_Dry_Index.
16. Klovland, J. T. (2004). Business Cycles, Commodity Prices and Shipping Freight Rates: Some Evidence from the pre-WWI Period. Paper presented at Workshop on Market Performance and the Welfare Gains of Market Integration in History, Florence, Italy.
17. LeBlanc, J. (2021). Suez Canal Blockage: Ripple Effect on Miami Valley Supply Chain. https://digitalcommons.cedarville.edu/business_administration_media_contributions/120/
18. Neha, M., Prashanth, D. (2018) The endemic issue of truck driver shortage – A comparative study between India and the United States. Research in Transportation Economics. https://doi.org/10.1016/j.retrec.2018.06.005.
19. Papailias, F, Dimitrios D.T., and Liu, J. (2017). The Baltic Dry Index: cyclicalities, forecasting and hedging strategies. Empirical Economics 52(1): 255-282. https://link.springer.com/article/10.1007/s00181-016-1081-9.
20. Sartorius, K., Sartorius B., and Zuccollo D. (2018). Does the Baltic Dry Index predict economic activity in South Africa? A review from 1985 to 2016. South African Journal of Economic and Management Sciences 21 (1): 1-9. http://dx.doi.org/10.4102/sajems.v21i1.1457.
21. Segal, E. (2021). Impact Of Suez Canal Crisis On Companies Around The World Could Last Weeks. Forbes. https://www.forbes.com/sites/edwardsegal/2021/03/31/impact-of-suez-canal-crisis-on-companies-around-the-world-could-last-weeks/?sh=6a0cb1042d8d.
22. SEOK-MIN LIM. (1998). Economies of scale in container shipping, Maritime Policy & Management, 25:4, 361-373. https://doi.org/10.1080/03088839800000059.
23. Suez Canal, Egypt. (2021). Earth Watching. https://earth.esa.int/web/earth-watching/image-of-the-week/content/-/article/suez-canal-egypt/.
24. Truelsch, M. (2021). The Suez Canal Ripple Effect. infor.com. https://www.infor.com/blog/the-suez-canal-ripple-effect.
25. Wen, P., Jing Y. (2021) Suez Canal Blockage Sends Asian, European Exporters Scrambling. The Wall Street Journal. https://www.wsj.com/articles/suez-canal-blockage-sends-asian-exporters-scrambling-11616771912.