# A Predictive Model for Transpacific Eastbound Ocean Freight Pricing

by

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ABSTRACT

The containerized ocean freight market has been very volatile due to overcapacity and several disruptive changes. As a global ocean freight forwarder, C.H. Robinson hopes to improve the predictability of the spot ocean freight rates, especially on the Transpacific Eastbound (TPEB) lanes which represent its largest trade volumes. Therefore, this research aims to build a predictive model for the TPEB spot freight rates using publicly available economic indicators and carrier data sources. Two predictive models corresponding to the US East Coast (USEC) routes and the US West Coast (USWC) routes are developed. The models for the China-origin routes are able to capture 69.0% of the variances in the USEC spot rates and 55.4% of the variances in the USWC spot rates. As an initial exploration, this research identifies 6 sets of critical economic indicators and unveils their effects on the TPEB spot rates. It also highlights the impact of 3 disruptive events and points out a few promising directions for future study on the ocean freight dynamics.


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Yan Huang

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## Table of Acronyms

| | |
|---|---|
| CPI | Consumer Price Index |
| GDP | Gross Domestic Product |
| MLR | Multiple Linear Regression |
| PMI | Purchasing Managers' Index |
| SCFI | Shanghai Export Containerized Freight Index |
| SEA | Southeast Asia |
| TPEB | Transpacific Eastbound |
| USEC | United States East Coast |
| USWC | United States West Coast |

## Glossary

| | |
|---|---|
| United States East Coast Ports | In this research, USEC ports include:<br>• East Coast 1: Port of Charleston (CHR) / Port of Savannah (SAV) / Port of Norfolk (ORF)<br>• Port of New York (NYC)<br>• Gulf<br>• East Coast 2: Port of Miami (MIA) / Port of Jacksonville (JAX) / Port of Baltimore (BAL) / Port of Boston (BOS) |
| United States West Coast Ports | In this research, USWC ports include:<br>• Pacific Northwest Port: Port of Tacoma (TIW)<br>• Pacific Southwest Port: Port of Los Angeles (LAX) |
| China based ports (CBP) | CBP ports also include those outside China but have the same freight rates<br>Shanghai (SHA) / Ningbo (NGB) / Qinghuangdao (QIN) / Yantian (YTN) / Shenzhen (SZX) / Hongkong (HKG) / Xiamen (XMN) / Busan (BUS) / Kaohsiung (KAO) / Keelung (KEE) |

# Chapter 1. Introduction

C.H. Robinson (CHR) is a world-leading third party logistics and supply chain management service provider with net revenue of $2.59 billion in 2019 (CHR, 2020a). Approximately 70% of its business focuses on the North American surface transportation (NAST), while global forwarding is its second largest but the fastest growing business category. Global forwarding in CHR consists of three types of services: ocean, air and customs-brokerage, contributing to 20% of its net revenue in 2019 (CHR, 2020a).

Ocean freight forwarding is the most critical global forwarding business for CHR. CHR operates as a Non-Vessel Operating Common Carrier ("NVOCC") and freight forwarder. It provides services in carrier selection, shipment consolidation, and routing optimization (CHR, 2020a). In 2019, ocean freight forwarding delivered $308 million net revenue (CHR, 2020a).

## 1.1. Background

In ocean freight forwarding business, CHR handles both long-term contracts and spot deals. It negotiates the spot rates with customers on a daily basis. Therefore, it is crucial for CHR to understand the dynamics of the ocean freight market and the key factors influencing the spot rates.

Such insights have become increasingly valuable in the past decade. The 2008 financial crisis disrupted the supply-demand balance in the containerized ocean freight market. Consequently, the market has been extremely volatile since then. Four main drivers behind this volatility are explained below:

1) Overcapacity

As the economy recovering from the financial crisis, the ocean carriers expected the demand to bounce back. To fulfill the anticipated demand and leverage the economies of scale, the carriers started to build mega vessels whose capacity is greater than 10,000 TEUs. As a result, from 2009 to 2018, the annual containership capacity had been growing at an average rate of 6.1% (Alphaliner, 2019a).

However, the market demand did not increase as what the ocean carriers had expected: Figure 1 shows the the twenty-foot equivalent unit (TEU) to Gross Domestic Product (GDP) growth multiplier, a prevailing measurement of the ocean container demand growth rate. During 1990 – 1999, the average of TEU-to-GDP Growth Multiplier was 3.4. It dropped to 2.6 during 2000 – 2008, and further decreased to 1.4 during 2010 – 2018 (Alphaliner, 2019b). The rapid increase in the shipping capacity and the slow demand growth eventually led to the severe overcapacity in the ocean market. This imbalance stimulated several major supply-demand adjustments, including surges of ship scrapping during 2016 – 2017 and the bankruptcy of Hanjin, a major Korean carrier, in 2017 (C.H. Robinson, 2019).

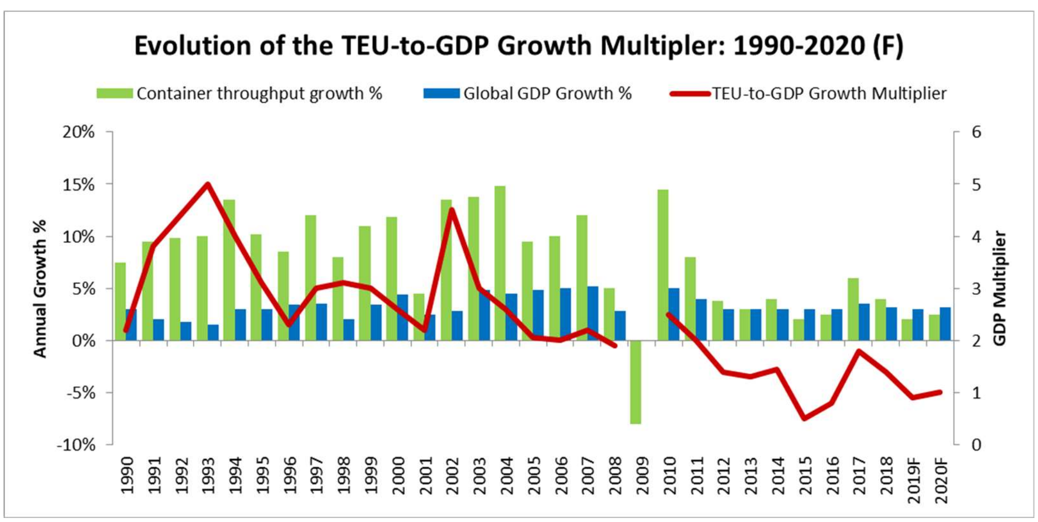



*Figure 1: Evolution of the TEU-to-GDP Growth Multiplier: 1990-2020. Adapted from Weekly Newsletter Volume 2019 Issue 32, by Alphaliner, 2019, https://www.alphaliner.com/.*

2) Carrier consolidation and alliances

To improve the financial situations in the over-supply market, the carriers opted to share the risks and investments via forming alliances, which could help them to attain greater flexibility in routings and achieve lower cost. In 2017, carrier consolidation and alliance formation reached a peak with 20 major carriers reduced to 12 (Laxmana, 2017). The consolidation drove the carriers to re-contemplate their value proposition to the customers and their relationships with the competitors. As a result, new ways of working were emerging (Tirschwell, 2019).

3) The rise of the East Coast

Traditionally, the exports from Asia, especially the Far East, including East and Southeast Asia, would discharge at the US West Coast (USWC), which is the closest route from Asia to the US. However, more and more vessels now arrive at the US East Coast (USEC) via Panama or Suez Canal instead (Miller, 2019). This swing in vessel routing is mainly driven by three factors:

1. The labor unrest on the West Coast in 2014 forced the importers to shift their shipments to the East Coast and they permanently stayed with that routing (Pinsker, 2015).
2. The demand in the US Southeast region is growing fast, as more and more people prefer moving to the Southeast for reasons such as the warm weather, the friendly tax policies and the rapid growth of job opportunities (North American Moving Services, 2019).
3. The expansion of the Panama Canal in 2016 allowed bigger and heavier ships to reach the East Coast (Link, 2017).

Hence, although USEC only possessed approximately one-third of the total US shipping capacity from 2014 to 2019 (CHR, 2019), it is playing an increasingly critical role in the US ocean market.

4) Government and industrial policies

The government and industrial policies, especially those would significantly influence the market demand or the maritime sector, have a great impact on ocean freight operations and rates. For example, the tariff war between the US and China since 2018 has been heavily affecting the volumes and freight rates on the Asia-US lanes. The higher tariffs might suppress the US imports from China, and thus the demand of the shipping services, by 10~15% (Cassidy, 2019). An example of the industrial policy is the "International Maritime Organization (IMO) 2020". Since January 2020, IMO, the entity overseeing the safety and environmental performance of the shipping sector under the United Nations, reduced the sulfur emission cap for ocean carriers from 3.5% m/m (mass by mass) to 0.5% m/m (CAI, 2017). Such regulation is estimated to increase the ocean carriers' cost by at least $15 billion per year (Posku, 2018).

Because of the volatile nature of the ocean logistics and the abovementioned disruptive changes, the ocean freight spot rates have been extremely challenging to predict. As a leading logistics service provider, CHR is motivated to improve the predictability of the spot rates and understand the key factors influencing the pricing dynamics.

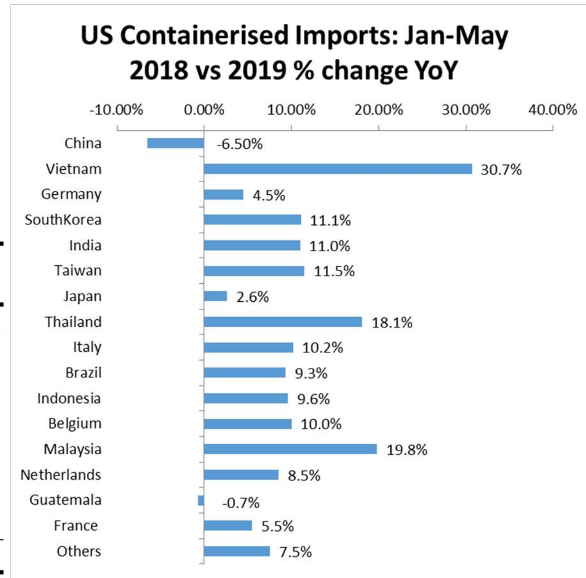
## 1.2. Motivation and Problem Statement

Due to the supply-demand imbalance and several disruptive events since 2008 financial crisis, the ability to interpret and predict the spot ocean freight rates has become more vital than ever.

As an initial exploration on the ocean freight market dynamics, this research mainly examines the roles of publicly available economic indicators. In terms of the geographic scope, the focus is on the Asia – US lanes, also known as the Transpacific Eastbound (TPEB) lanes, because the China – US lanes carry the largest trade volumes in the word (Figure 2a), while a few Southeast Asian countries, namely Vietnam, Thailand, and Malaysia, are displaying the greatest growth potential (Figure 2b).

Breakdown by Region

| In TEU Millions by Origin | Jan - May 2018 | Jan - May 2019 | % change |
|---|---|---|---|
| Far East | 6.103 | 6.121 | 0.3% |
| *China* | 4.139 | 3.871 | -6.5% |
| *Far East exc China* | 1.964 | 2.250 | 14.6% |
| Europe | 1.451 | 1.568 | 8.1% |
| Latin America | 0.913 | 0.973 | 6.6% |
| ISC/Middle East | 0.459 | 0.506 | 10.3% |
| Oceania | 0.083 | 0.083 | 0.7% |
| Africa | 0.050 | 0.057 | 14.3% |
| Total | 9.058 | 9.308 | 2.8% |




*2a* *2b*

*Figure 2: US containerized imports Jan-May 2019 vs Jan-May 2018: global distribution (2a) and growth rate (2b). Adapted from Weekly Newsletter Volume by Alphaliner, 2019, https://www.alphaliner.com/.*

This research will contribute to the understanding of the TPEB spot market dynamics by:

1) Identifying the economic indicators influencing the TPEB spot freight rates and discussing their effects both quantitatively and in a business context;
2) Building a model to predict the spot freight rates with the economic indicators.

We concentrate the modeling and discussion on the China – US routes, while we also briefly explore the routes starting from six Southeast Asian countries, namely the Philippines, Malaysia, Singapore, Thailand, Vietnam and Indonesia. First, we conducted a literature review to develop a list of candidate indicators affecting the ocean freight rates. Then, we collected the data for each indicators of interest at its lowest available granularity and performed correlation analysis to quantify the relationship between individual indicators and the ocean freight rates. Thereafter, we created statistical regression models based on various economic indicators to predict the spot freight rates. The models were visualized and economic indicators with critical influence were identified and discussed. Finally, we examined the modeling outcomes in a business context to provide managerial insights to CHR.

# Chapter 2. Literature Review

To understand the factors influencing the TPEB ocean market dynamics and establish a model to predict the spot rates, we performed a literature review to:

1) Identify a range of parameters that potentially affect the TPEB ocean freight rates; and
2) Determine the most appropriate predictive model and its data processing requirements.

## 2.1. Factors Influencing Ocean Freight Rates

Although we focus on the influence of economic indicators on the ocean freight rates in this research, we conducted a thorough literature review to examine all the factors that could affect the ocean freight rates, so that we could develop a holistic understanding of the ocean freight market and ensure that the research scope was not unreasonably simplified.

### 2.1.1. Economic and Social Factors

Marx (1946) examined the impact of World War I on ocean freight rates in Western Europe and he highlighted four key factors influencing the rates: 1) the excess supply of shipping capacities; 2) the change in demand driven by economic factors such as GDP and the employment rates; 3) the cost of operating vessels, which is often influenced by fuel cost and volume consolidation; and 4) social factors and policies, such as the wars. These four factors correspond well with the market changes since the 2008 financial crisis: the drastic supply-demand imbalance resulting from the rapid increase in shipping capacities and the sluggish growth in demand (Figure 3) has been fundamentally propelling the complexities of the current ocean freight market. In addition, economic policies such as the US – China tariff war and the industrial policies further instilled uncertainties into the market.

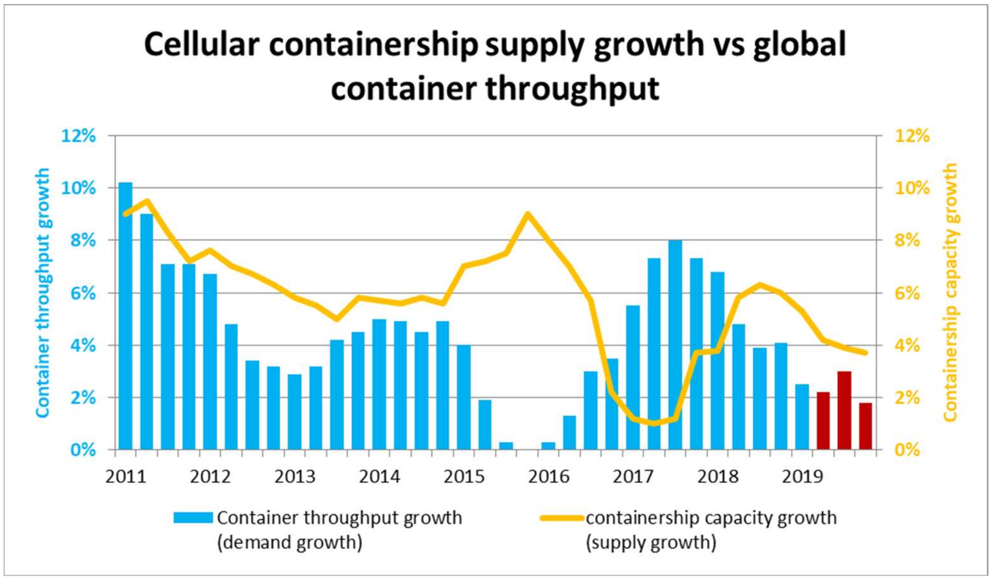



*Figure 3: Container throughput growth (demand) vs. containership capacity growth (supply). Adapted from Weekly Newsletter Volume 2019 Issue 21, by Alphaliner, 2019, https://www.alphaliner.com/.*

While most of Marx's (1946) discussions are qualitative, Klovland (2008) quantitatively evaluated the impact of supply, demand and social events on ocean freight rates in the 1850s. By integrating freight rate index, price level, world tonnage and trends of demand changes into an econometric model, Klovland (2008) argued that Crimean War and people's anticipation of the war had great impact on ocean freight rates – the rates were largely increased before the war and drastically dropped after it. He also pointed out that the freight rate fluctuation coincided with business cycles. Although Klovland's research (2008) focuses on the ocean freight market in the 1850s and the Crimean War, it uncovers the vital roles that macro-economic environments and public anticipation play in the ocean market dynamics. As a result, in our research, we investigate the influence of a few critical events, including Panama Canal expansion (2016), US – China trade war (2018 – present) and IMO 2020, on the TPEB freight rates, because these events have altered the economic environment and the public anticipation of the ocean freight market in the past decade.

Another economic factor highlighted in the literature is the exchange rate. Chi (2016) examined ocean freight flows between the US and China and concluded that exchange rates affect the freight flows significantly by influencing the transportation cost. According to Chi, a US dollar (USD) appreciation against the Chinese yuan (CNY) increases the inflows of Chinese commodities to the US.

### 2.1.2. Operational Factors

Apart from the economic and social factors, some literature explored the relationships between operational parameters and the ocean freight rates. Binkley and Harrer (1981) discovered that shipping distance, ship size and trade volumes are equally important in determining the freight rates. Ding (2012) and Yunianto (2018), having focused on on-shore operations, identified correlations between freight rates and operational factors such as port waiting time, ease of customs clearance and other operating costs at the ports.

In summary, the literature shows that the freight rates are influenced by 4 categories of factors (Appendix A):

1) Supply: changes in shipping capacities;
2) Demand: economic indicators such as GDP and Consumer Price Index (CPI), currency exchange rates, business cycles and the public anticipation of the economic environments;
3) Operating costs: the bunker fuel cost, shipping distance, ship size and costs at port; and
4) Disruptive events, such as the financial crisis, canal expansion, trade war and the maritime policies.

## 2.2. Predictive Modeling

Silver, Pyke and Peterson (1998) classified forecast modeling into two main categories: statistical forecasting and judgmental forecasting. Statistical forecasting relies heavily on interpreting the historical data, while judgmental forecasting predicts the future with the current known factors. Makridakis (1986) suggested that a predictive model developed solely from judgmental forecasting is not trustworthy because of its over-emphasis on the qualitative analysis. Since the data inputs for this research, including ocean freight spot rates and various published economic indicators, are all historical, we adopt statistical forecasting.

### 2.2.1. Multiple Linear Regressions (MLR)

Elarbi (2013) further categorized statistical modelling into four methods: qualitative analysis, time-series analysis, causal analysis and simulation, among which multiple linear regression (MLR) is one of the simplest and most common modeling techniques to estimate the relationships between a target and multiple features. The outcome of MLR is a linear equation as shown in Equation 1 (Laerd Statistics, 2018).

$$\mathrm{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \qquad (1)$$

Features are also known as the independent variables, usually denoted by symbol “x” (Stewart, 2011). They are the controlled inputs of the model. In this study, the features are various economic indicators that potentially affect the ocean freight rates. N is a positive integer (i.e., 1, 2, 3…) to label the features (i.e., economic indicators) so that they can be uniquely identified in Equation 1.

A target is also known as a dependent variable, usually denoted by symbol “y” (Stewart, 2011). It is the model output and the variable that a MLR model tries to predict for. In this study, the target is the TPEB ocean freight spot rate. The target and the features are discussed in detail in Section 3.1.1 and 3.1.2.

The model coefficient (β) indicates how much the target (i.e., the ocean freight rate) varies with a specifics feature (i.e., an economic indicator) when all other features (i.e., other economic indicators) are held constant (Laerd Statistics, 2018). The magnitude of β (i.e., the absolute value of β) weighs the extent of influence for each economic indicator on the ocean freight spot rate: The larger the absolute value of β is, the greater influence the corresponding economic indicator has over the ocean freight spot rate. The sign of β (i.e., whether the β is positive or negative) shows if a change in the economic indicator would support or depress the freight rates. For an economic indicator with a positive β, an increase in the indicator will raise (i.e., support) the freight rates, while for an economic indicator with a negative β, an increase in the indicator will decrease (i.e., depress) the freight rates.

### 2.2.2. Data Requirements for MLR

To obtain robust results for MLR, the data inputs should fulfill the following requirements (Laerd Statistics, 2018):

1) All the observations should be made independently; that is, the value of any variable cannot influence that of the variable in other observations (Kent State University, 2020);
2) The target variables should be measured on a continuous scale; that is, they should be numerical data that can theoretically be measured in infinitely small units (Laerd Statistics, 2018);
3) The features should be measured on either a continuous or a categorical scale; a categorical scale means that the data have two or more groups (Laerd Statistics, 2018), while a continuous scale has been illustrated in point 2);
4) There should be linear relationships between the features and the targets;
5) The features should be normally distributed;
6) There should be no significant outliers; and
7) The features should not show multicollinearity; that is, the features should not have strong linear correlations with each other. Multicollinearity is not desirable since it will

introduce bias into the model and thus make the results less accurate (StatisticsSolutions, 2020). This requirement leads to the following study on Pearson Correlation Test.

### 2.2.3. Pearson Correlation Test

Correlation describes the relationship between two quantitative and continuous variables. Pearson correlation test is a bivariate correlation test developed by Karl Pearson based on a related idea introduced by Francis Galton in the 1880s (Pearson, 1895). In this research, we performed Pearson correlation test to:

1) Explore the relationship between each economic indicator (i.e., feature) and the ocean freight rates (i.e., target); and
2) Identify and remove the multicollinearity among the features, as required in Section 2.2.2, to minimize the bias in the data inputs.

The key output from the Pearson correlation test is the correlation coefficient r, which varies from -1 to 1: when $r = -1$, the pair of features has a perfect negative linear relationship, which means that as one variable increases in its values, the other variable decreases according to an exact linear rule; when $r = 1$, the pair of features has a perfect positive linear relationship, which means that as one variable increases in its values, the other variable also increases, according to an exact linear rule; and when $r = 0$, the pair of features has no relationship (Ratner, 2009).

There are multiple sets of standard to classify weak, moderate and strong correlations. Relatively stringent criteria assess the strength of the correlations as below (Cohen, 1988):

0.1 < absolute value of r < 0.3: weak correlation

0.3 < absolute value of r < 0.5: moderate correlation

0.5 < absolute value of r <1: strong correlation

A more prevailing assessment differentiates a moderate and strong correlation at r = 0.7 (Ratner, 2009), that is:

0.0 < absolute value of r < 0.3: weak correlation

0.3 < absolute value of r < 0.7: moderate correlation

0.7 < absolute value of r < 1.0: strong correlation

### 2.2.4. Stepwise Regression – A Specific MLR Suitable for This Research

After understanding the requirements for data processing, we studied the MLR model in detail and identified stepwise regression as the most suitable MLR for this research because of below two advantages:

1. Stepwise regression is able to identify a subset of features that have significant relationship with the target. It allows us to strike a good balance between two conflicting objectives in this research: 1) integrating as many relevant features as possible in order to develop a comprehensive and realistic model; and 2) minimizing the number of variables involved to avoid over-complicating the model and increasing the burden of data maintenance without improving the model accuracy (NCSS, 2020).

   One of our goals in this research is to understand which features, among a pool of candidates, significantly affect the TPEB spot freight rates. Instead of incorporating all the features into the model, stepwise regression achieves the research goal by recognizing the significant features and building a predictive MLR only with them.

2. Stepwise regression always resolves multicollinearity and thus reduces the bias in the model. The stepwise regression result always contains a term called Variance Inflation Factor (VIF). In statistics, VIF suggests how much error in an estimated regression coefficient (i.e., β introduced in Section 2.2.1) attributes to the correlations among the features (James et al.,

2017). The VIF of all the coefficients in the stepwise regression results should be kept within 0.1 to 10 to ensure the independency of the variables (StatisticsSolutions, 2020). This means that any parameter with a VIF outside the range should be removed to minimize the bias in the regression results.

As the stepwise regression is a type of MLR, its outcome is represented by Equation 1. The accuracy of the stepwise regression model is evaluated by R-square ($R^2$), which represents the proportion of the variances in the spot freight rates that could be explained by the model. Its formula is shown in Equation 2:

$$R^2 = 1 - \frac{Unexplained\ Variation}{Total\ Variation} \quad (2)$$

### 2.2.5. Standard Regression – Improving the Stepwise Regression Results

Unlike the stepwise regression, the standard (i.e., default) regression keeps all the features in the model to account for even the remote effects they have on the features (NCSS, 2020). Therefore, the standard regression might be able to improve the modeling performance when the stepwise regression returns poor results.

## 2.3. Gaps to Be Closed

The literature review provides a holistic overview of the existing studies on factors affecting the ocean freight rates. However, the literature has two major gaps which this research aims to close:

### 2.3.1. Geography: The US Ocean Freight Market and the TPEB Lanes

Most of the literature focuses on the Western European and the Asian ocean freight markets. However, according to CHR, the ocean freight forwarding operation in the US can be very different from those in the Europe and Asia, especially when considering the transformational changes driven by regional events such as the 2014 labor unrest on the US West Coast and the

2016 expansion of Panama Canal. Therefore, it is necessary to systemically investigate the US ocean freight market, which is the focus of our research.

Moreover, there is scarce literature particularly focusing on the TPEB lanes. As shown in Figure 2, TPEB lanes have become increasingly important in the global ocean freight network due to the rapidly growing trading opportunities between the Far East, including East and Southeast Asia, and the US. Along with the opportunities, the dynamics of the TPEB lanes also become sophisticated to understand and predict. Therefore, we aim to primarily unveil the market dynamics particularly for the TPEB lanes through this research.

### 2.3.2. Time: Post 2008 Financial Crisis

Financial crisis has disrupted the supply-demand balance and stimulated a few long-term changes, including the overcapacity in the shipping market and carrier alliances. However, there is little visibility on how the market has been responding to the economic environments after the 2008 financial crisis. We aim to provide some primary insights on such queries.

# Chapter 3. Data and Methodology

The main objectives of this research are to explore the relationships of various economic indicators with the TPEB ocean freight spot rates and to build an MLR model to predict the rates. The key steps to perform the research include:

1) Collecting the data;
2) Cleaning and transforming the data to prepare for the Pearson correlation analysis and MLR modelling; performing the Pearson correlation analysis to remove the strongly correlated features while primarily detecting the relationship between each economic indicator and the ocean freight rates;
3) Building the predictive models via stepwise regression and discovering the economic indicators with critical influence;
4) Improving the models for Asia – USWC lanes with standard regression.

Each step will be discussed in Sections 3.1 through 3.4 below:

## 3.1. Data Collection

### 3.1.1. The Modelling Targets: CHR TPEB Spot Rates and Shanghai Export Containerized Freight Index (SCFI)

The raw data for the main target variable in this research are the daily ocean freight spot rates ($/TEU) of CHR from April 2014 to August 2019. The original dataset contains around 6 million records of the spot freight rates across all the TPEB routes in CHR. We grouped the TPEB lanes of interest (Table 1) and classified the raw data corresponding to the lanes. We examined the lanes to the US West Coast (USWC) and the US East Coast (USEC) separately because the

USEC is further from Asia and thus its freight rates are structurally \$1000 – \$2000 per TEU higher than those from Asia to the USWC (Lopez, 2018).

*Table 1: TPEB lanes studied in this research*

| No. | Country of Origin | Ports of Origin | Destination |
|---|---|---|---|
| 1 | China (CN) | All China-based ports | USEC<br>USWC |
| 2 | Indonesia (ID) | Jakarta (JKT) | |
| 3 | The Philippines (PH) | Manila (MNL) | |
| 4 | Singapore (SG) | Singapore (SG) | |
| 5 | Thailand (TH) | Port of Laem Chabang (LCH) | |
| 6 | Malaysia (MY) | Port of Port Klang (PKG) | |
| 7 | Malaysia (MY) | Port of Tanjung Pelepas (TPP) | |
| 8 | Vietnam (VN) | TOT | |
| 9 | Vietnam (VN) | Port of Saigon (SGN) | |

Apart from exploring the dynamics of the CHR spot rates, we also modelled and analyzed the public market spot rates to ensure that the insights derived from CHR spot rates are applicable to a broader shipping community. CHR gauges the TPEB market rates, especially the China – US rates, with the Shanghai Export Containerized Freight Index (SCFI), a weekly published spot rate index based on Shanghai export container transport market (SSE, 2020). Therefore, we collected SCFI for China (port Shanghai) – USWC ports (including New York, Savannah, Norfolk and Charleston) and China (port Shanghai) – USEC ports (including Los Angeles, Long Beach and Oakland). The results on SCFI modeling are analyzed in Section 5.6.

### 3.1.2. The Modelling Features: Economic Indicators

As summarized in Section 2.1, the ocean freight rates can be influenced by various parameters including the shipping capacity, economic indexes, operational costs and disruptive events. Based on the data accessibility and the discussion with CHR, nine parameters were deemed relevant to this research (Appendix B). Table 2 elaborates the details and assumptions of the parameters with a focus on the China – US lanes. The same data collection methodology was adopted for Southeast Asia (SEA) – US lanes.

*Table 2: Feature details for the China – US lanes*

| No. | Indicators | Source | Granularity | Assumption |
|---|---|---|---|---|
| 1 | GDP (US) | U.S. Bureau of Economic Analysis | Quarterly | Nominal |
| 2 | GDP (CN) | National Bureau of Statistics of China | Quarterly | |
| 3 | CPI (US) | Bureau of Labor Statistics | Monthly | Non-Seasonally Adjusted (NSA) |
| 4 | CPI (CN) | National Bureau of Statistics of China | Monthly | |
| 5 | Oil Price | NASDAQ | Daily | |
| 6 | Currency Exchange Rate | Investing.com | Monthly | The amount of Chinese Yuan (CNY) equivalent to 1 US Dollar (USD) |
| 7 | Shipping capacity | CHR | Annual | USWC and USEC |
| 8 | PMI* (US) | Institute For Supply Management | Monthly | Manufacturing PMI |
| 9 | PMI* (CN) | | | |

**PMI: Purchasing Managers' Index*

Table 3 summarizes the data availability and assumptions according to the countries.

*Table 3: Data availability for the economic indicators across all the countries of origin*

| Parameters | CN | ID | SG | TH | PH | MY | VN |
|---|---|---|---|---|---|---|---|
| Currency Exchange Rate (monthly) | Y | Y | Y | Y | Y | Y | Y |
| CPI (monthly) | Y | Y | Y | Y | Y | Y | Y |
| GDP ($, quarterly) | Y | Y | N | Y (2019Q3) | Y (2019) | Y (2019) | N |
| PMI (monthly) | Y | Y | Y | N | Y (PISM 2014) | N | N |
| **Assumption Summary (after removing outliers)** | | | | | | | |
| Time Period | 201404-201908 | 201404-201908, | 201404-201908 | 201404-201906 | 201501-201812 | 201404-201812 | SGN: 201408-201908;<br>TOT: 201505 - 201908 |
| Number of Data Points | 61 | 58 | 55 | 52 | 43 | 52 | SGN: 57<br>TOT: 47 |

*Y: yes, available; N: no, not available; Y ( ): yes, available but missing data indicated in the parentheses.*

Apart from the nine parameters listed in Table 2, several disruptive events, namely the Panama Canal expansion (2016), the China–US tariff war (2018–present) and the IMO 2020 also stimulated short-term oscillation in the ocean freight market. We discussed their effects on the ocean freight spot rates in Section 5.4.

### 3.1.3. The Granularity of This Research

Table 2 shows that the features (e.g., the economic indicators) have distinct granularity levels ranging from daily to annual. Such variation results either from the different official data publishing frequency or from the limitations on the data availability.

We determined the granularity of this research to be monthly. There were two main reasons: 1) compared to a study on an annual or a quarterly level, the study at the monthly granularity allowed us to preserve more data points and thus incorporate more details of the market variations into the predictive models; 2) studying the freight rates on the daily level would require us to excessively duplicate the annual or quarterly economic indicators to fill the missing daily data, which would introduce significant inaccuracies and complexities into the models. To avoid such disadvantages, we decided to keep our analysis on a monthly level.

To unify the data granularity, data originally available at a daily or weekly frequency were converted to monthly values by taking the median of each month. Data originally available at quarterly and annual levels were evenly populated across the months.

## 3.2. Data Cleaning and Transformation

Section 2.2.2 displays the data input requirements for the MLR modeling.

In this research, the datasets of the targets (i.e., ocean freight rates) and the features (i.e., the economic indicators) intrinsically fulfill criteria 1) – 3) in Section 2.2.2: the observations of spot freight rates and economic indicators are independent, because one reading does not affect another; all the targets and the features are numerical values measured on a continuous scale.

For criteria 4), we assumed to explore the linear relationships between the spot rates and the economic indicators. This research is an initial exploration of the TPEB ocean market dynamics, assuming a linear relationship between the target and features could simplify the problem and provide both meaningful primary insights and the hints on future research directions.

Therefore, we performed data cleaning mainly to make the data comply with criteria 5) – 7) in Section 2.2.2, including checking the normal distribution of the features, removing the outliers and minimizing the multicollinearity among the features. Detailed steps are illustrated in Section 3.2.1, 3.2.2 and 3.2.3.

### 3.2.1. Data Re-scaling and Standardization

*3.2.1.1. Data Re-scaling*

In this research, the features and targets have distinct values and ranges. Consequently, the features with much larger values or ranges might dominate the analysis, resulting in an unfair comparison. Therefore, before normalization, we performed mean rescaling (Equation 3) to ensure that all the variables were compared on a common scale.

$$x_{scaled} = \frac{x - average(x)}{\max(x) - \min(x)} \tag{3}$$

*3.2.1.2. Data Standardization*

A dataset can be transformed into a normal distribution (e.g., a bell curve) via standardization. To understand the intrinsic normality of the data, we first performed the Shapiro-Wilk test, a common test of normality in statistics, in Statistical Product and Service Solutions (SPSS) on both the original and the re-scaled datasets. In Shapiro-Wilk test, data are normally distributed if the significance of the Shapiro-Wilk test is greater than 0.05 (Shapiro, 1965).

The testing results suggest that both the original and the re-scaled datasets have 6 out of 12 features normally distributed. We also noted that data standardization distorts the nature of the data distribution because it forces all kinds of data into a bell-curve distribution. Such distortion is detrimental to this research because it makes the subsequent predictive modeling and business interpretation less accurate and representable (Lakshmanan, 2019). Therefore, to balance between the requirements for the model inputs and the meaningfulness of the business insights, we proceeded with the mean re-scaled dataset with 50% normality in this research.

### 3.2.2. Removing the Outliers

To minimize the influence of the extreme values, we adopted the z-score analysis to identify and remove the outliers from the datasets.

Z-score denotes the number of standard deviations that a data point is away from the mean of the group (Bradburn, 2020) (Equation 4).  In order to preserve the maximal number of data points for the subsequent modeling while minimizing the bias from the outliers, we set a z-score of 2.326, denoting a 98% confidence level, as the threshold of removal: If an entry had one or more data points with an absolute z-score greater than 2.326, then we removed the entire entry.

$$\mathrm{z} = \frac{x - me \quad (x)}{standard\ deviation\ (x)} \tag{4}$$

The last row in Table 3 at Section 3.1.2 lists the number of data points flowing into the modeling for each route after the outliers were removed.

### 3.2.3. Removing Features with Strong Correlations – Pearson Correlation Test

As introduced in Section 2.2.3, to minimize the bias introduced by the correlations among the features, we had to remove features with strong correlations.

We detected the pairwise correlation among all the variables via the Pearson correlation test in SPSS. To preserve the most number of features for the subsequent modeling, we adopted the more prevailing standard in Section 2.2.3, which means we only removed the features with correlation coefficients (r) greater than 0.7.  If multiple features were strongly correlated, we would only keep the one displaying the strongest correlation with the ocean freight rates.

Apart from moving the strongly correlated features, we also learnt about the relationship between individual indicators and the ocean freight rates via Pearson correlation test. We present relevant analysis in Section 4.1.2 (data-oriented) and Section 5.1 (with a business context).

## 3.3. A Multiple Linear Regression Model - Stepwise Regression

After rescaling, removing the outliers and eliminating the strong correlations, the features and the targets were ready for the multiple linear regressions (MLR) modelling.

As introduced in Section 2.2.4, we started with the stepwise regression because apart from building the predictive model, it could identify the critical features and further detect the multicollinearity in the regression coefficients β.

The key settings for the stepwise regression in SPSS are:

- Linear regression statistics:
  - Regression coefficients: estimate, confidence level: 99%
  - Model fit, collinearity diagnostics (to detect multicollinearity)
- Linear regression options:
  - Significance of adding a variable: < 0.05
  - Significance of removing a variable: > 0.1
  - Exclude cases pairwise when there is missing value

## 3.4. Model Improvement – Standard Regression for USWC lanes

We observed that the stepwise regression performed poorly for all the TPEB lanes to the USWC ($R^2 = 0.1 – 0.3$). To improve the model (Section 2.2.5) , we adopted the standard regression to re-model all the USWC lanes. To minimize the complexity and bias in the model, we only fed those variables identified significant via the USEC stepwise regression into the USWC standard regression models.

# Chapter 4. Results and Discussion

In this research, we first explored the relationships between individual economic indicators and the TPEB ocean freight spot rates based on the Pearson correlation test results. Then, we predicted the spot freight rates with the critical indicators identified via stepwise regression modelling. As the China – US lanes account for the majority of the trade volumes on the TPEB lanes (Figure 2, Section 1.2), we focus on interpreting the results for the China – US lanes, while we briefly discuss the models for the Southeast Asia (SEA) – US lanes.

In this section, we will present and analyze the research results in the following four aspects:

1) The correlation analysis among the features: A summary of the parameters removed from the MLR modelling due to the strong correlations;
2) Understanding the correlations between the individual parameters and the spot rates;
3) Predicting the USEC spot freight rates for TPEB lanes via MLR stepwise regression; and
4) Predicting the USWC spot freight rates for TPEB lanes via MLR standard regression.

## 4.1. The China – US Lanes

### 4.1.1. Removing the Features with Strong Correlations

As mentioned in Section 3.2.3, we performed pairwise Pearson correlation test to remove the strongly correlated features. If multiple features displayed strong correlation ($r > 0.7$), we kept the one displaying the strongest correlation with the spot freight rates.

Table 4 shows that for China – US lanes, US CPI, US GDP, China GDP and WC capacity had strong pairwise correlations with $r > 0.7$. We kept US CPI and WC capacity because US CPI had the strongest correlation with the USEC spot rate (-0.254) among the four parameters, while WC capacity had the strongest correlation with USWC spot rate (0.129) among the four.

*Table 4: Removing strongly correlated features in the data for the China – US lanes*

| Indicators | Correlated Indicators | Correlation with USWC Freight | Correlation with USEC Freight | Decision |
|---|---|---|---|---|
| US CPI | China GDP (0.876**)<br>US GDP (0.987**)<br>WC capacity (0.863**) | 0.070 | -0.254* | Keep |
| US GDP | US CPI (0.987**)<br>China GDP (0.883**)<br>WC capacity (0.876**) | 0.065 | -0.242 | Remove |
| China GDP | US CPI (0.876**)<br>US GDP (0.883**) | 0.090 | -0.238 | Remove |
| WC capacity | US CPI (0.863**)<br>US GDP (0.876**) | 0.129 | -0.085 | Keep |

### 4.1.2. Correlations between Each Feature and the Spot Ocean Freight Rates

To explore the potential effects of each economic indicator on the ocean freight spot rates, we examined the correlations between the individual indicator and the freight rates for both China – USEC (Table 5) and China – USWC (Table 6) lanes.

*Table 5: Pairwise correlations between the economic indicators and the China – USEC spot rate*

| Rank | Economic Indicators (scaled) | Correlation with Freight r (scaled) |
|---|---|---|
| 1 | Currency Exchange Rate (1USD) | -0.420** |
| 2 | Oil Price | 0.335** |
| 3 | EC Shipping Capacity | 0.322* |
| 4 | US CPI (NSA) | -0.254* |
| 5 | US GDP | -0.242 |
| 6 | China GDP | -0.238 |
| 7 | China CPI (NSA) | -0.231 |
| 8 | US PMI | 0.168 |
| 9 | China PMI | -0.166 |
| 10 | WC Shipping Capacity | -0.085 |

***: 99% significant; *: 95% significant*

*Table 6: Pairwise correlations between the economic indicators and the China – USWC spot rate*

| Rank | Economic Indicators (scaled) | Correlation with Freight r (scaled) |
|---|---|---|
| 1 | Oil Price | 0.494** |
| 2 | US PMI | 0.346** |
| 3 | WC Shipping Capacity | 0.129 |
| 4 | China GDP | 0.090 |
| 5 | US CPI (NSA) | 0.070 |
| 6 | Currency Exchange Rate (1 USD) | 0.066 |
| 7 | US GDP | 0.065 |
| 8 | China PMI | -0.021 |
| 9 | China CPI (NSA) | 0.010 |
| 10 | EC Shipping Capacity | 0.001 |

***: 99% significant; *: 95% significant*

Among all the indicators, only oil price displayed relatively strong correlations with both the USEC and USWC spot rates, while the rest were all weakly correlated with the spot rates.

In the next two subsections, we further examine the economic indicators displaying top correlations with the China –USEC spot rates (Section 4.1.2.1) and the China –USWC spot rates (Section 4.1.2.2).

*4.1.2.1. The Correlation Analysis for the China –USEC Spot Market*

The top three features correlated with the USEC freight rates are (Table 5):

– The currency exchange rate (CNY per USD), at a moderate correlation of -0.420;

– The oil price, at a moderate correlation of 0.335; and

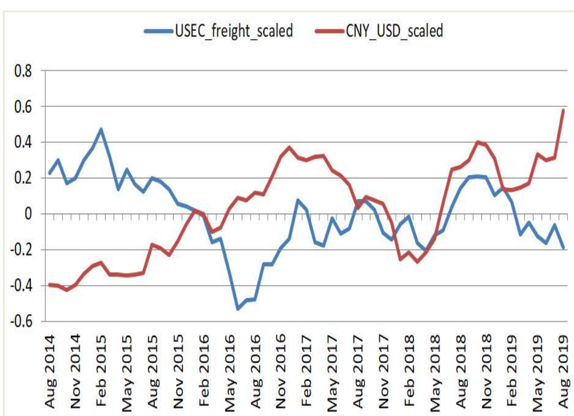
– The EC shipping capacity, at a moderate correlation of 0.322.

All of the coefficients are at either 99% (**) or 95% (*) significance levels, indicating that the test is confident about the correlation coefficients at 95% or higher.

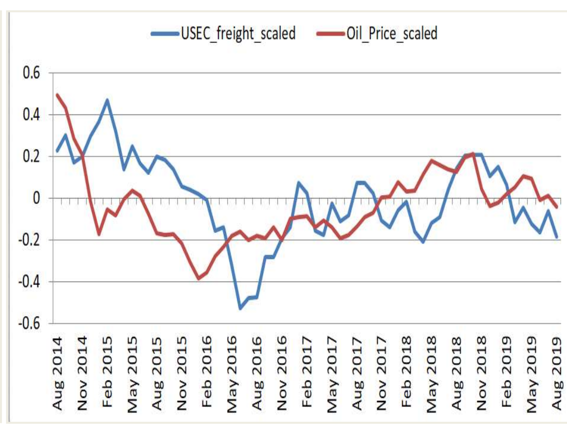
**1) Currency Exchange Rate and the China – USEC Spot Rate**

The currency exchange rate is correlated with the China – USEC spot rate at a coefficient (r) of -0.420, which suggests that the currency exchange rate and the USEC freight rate overall move in opposite directions: When the currency exchange rate rises, i.e., when USD appreciates against CNY, the ocean freight rates might decrease; conversely, when the currency exchange rate drops, i.e., the USD depreciates against CNY, the ocean freight rates might increase.

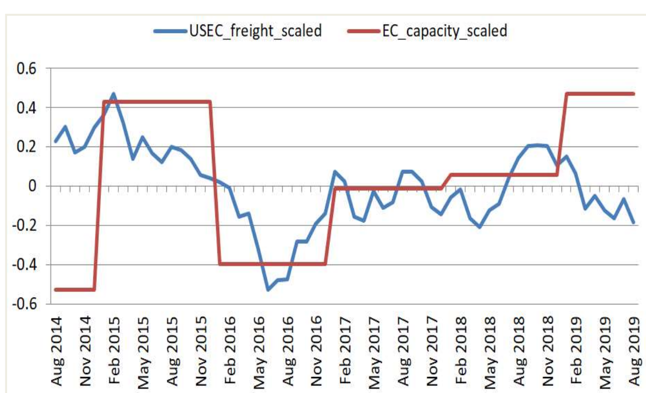
The actual movement of the currency exchange rate and the USEC freight rates from August 2014 to August 2019 is plotted in Figure 4a. We can observe the opposite movement from May 2015 to May 2016 and from February 2019 onwards, while during the rest of the time, the movement is more synchronized towards the same direction.




*4a. Currency exchange rate (CNY per USD)*




*4b: Oil price*




*4c: EC shipping capacity*

*Figure 4: Visualization of the top three indicators correlated with the China –USEC ocean freight spot rate*

**2) Oil Price and the China – USEC Spot Rate**

Oil price has a positive correlation coefficient (r=0.335) with the China – USEC ocean freight rate, indicating that the oil price and the freight rate might move in the same direction — when the oil price increases, the ocean freight rate also increases; when the oil price drops, the ocean freight rate also moves downwards. Figure 4b shows that indeed, from 2014 to 2019, the movement of the two variables was largely in the same direction. However, the movement was not synchronized – oil price (red line) seems to move first, followed by the freight rate (blue line). Such trend is particularly explicit during May 2015 to August 2016. This dis-synchronization might have resulted in the low correlation coefficient value. However, it also suggests that the oil price might be a leading indicator for the China –USEC ocean freight spot rate. This hypothesis is analyzed in detail in Section 5.2.

**3) EC Shipping Capacity and the China – USEC Spot Rate**

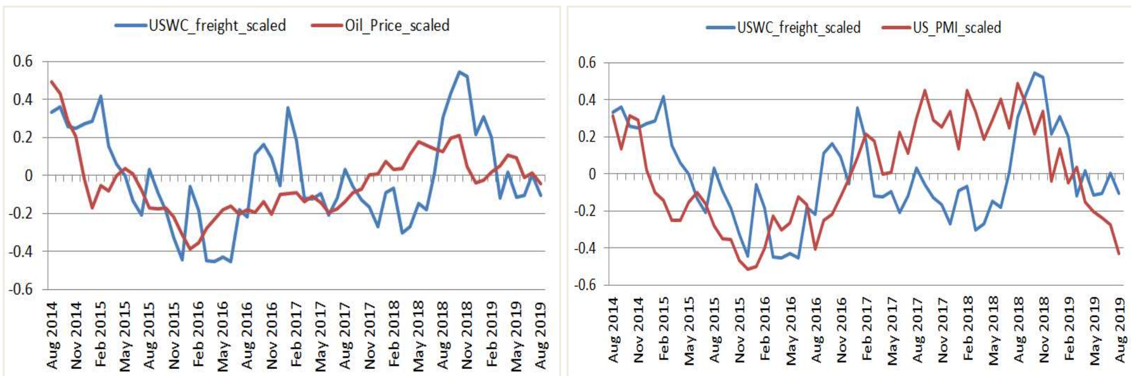
Same as the oil price, EC shipping capacity also displays a positive moderate correlation (r = 0.322) with the China – USEC spot rate, indicating that the two variables move in the same direction. The actual data plotted in Figure 4c again verifies such an inference. However, as the EC shipping capacity data were only available at the annual level, it is difficult to examine the correlation of EC shipping capacity with the China – USEC spot rate in greater detail. This challenge might explain why the correlation coefficient is only at 0.3.

*4.1.2.2. The Correlation Analysis for the China –USWC Spot Market*

Oil price and the US PMI display moderate correlations with the USWC spot freight rate, at r = 0.494 and r = 0.346 respectively, both at 99% confidence level.

**1) Oil Price and the China – USWC Spot Rate**

Similar to the China – USEC lane, oil price is positively correlated with the USWC freight rate, suggesting that the oil price and the USWC spot rates increase or decrease in the same direction. Figure 5a visualizes their actual historical movement and the plot supports the inference on the same-direction movement. However, differently from the China – USEC, oil price does not display an explicit leading effect against the China – USWC spot rate, though more quantitative study is required to verify this hypothesis.




*5a: Oil price* *5b: US PMI*

*Figure 5: Visualization of the top two indicators correlated with the China –USWC ocean freight spot rate*

**2) US PMI and the China – USWC Spot Rate**

US PMI is weakly correlated with the China – USEC freight rate (r=0.168) but moderately correlated with the China – USWC freight rate (r = 0.346). A positive r shows that when the US PMI increases, the USWC freight rate increases as well, which is in line with the actual movement (Figure 5b) at most of the time. However, during the February to August 2016 and May 2017 to May 2018 periods, the US PMI seems to move more in an opposite direction with the USWC freight rate.

Via the correlation analysis, we primarily unveil the relationship and dynamics between each economic indicator and the ocean freight rates. However, it is worth noticing that such analysis is not sufficient to quantitatively determine the effect of each indicator on the ocean freight spot rates. It also cannot determine the causal relationships. To fully understand the relationship between a specific economic indicator and the ocean freight rates, we suggest conducting more rigorous statistical analysis in future.

### 4.1.3. A Predictive Model for the China – USEC Spot Freight Rate

After exploring the relationship between individual parameters and the ocean freight rates, we examine the combined effects of all the parameters via MLR modeling. A predictive model for the China – USEC freight rates was established via the stepwise regression. Equation 5 presents the formula and Figure 6 visualizes the predicted China – USEC spot rates against the actuals from CHR. The model achieves an $R^2$ of 0.690, meaning that 69% of the variances in the China – USEC spot freight rate can be explained by the model. In below subsection, we analyze the critical parameters affecting the China – USEC spot rate (Section 4.1.3.1) and evaluate the predictive model (4.1.3.2).

$$\textit{China-USEC Spot Freight Rate} = 0.013 - 0.741 * \textit{US CPI} + 0.544 * \textit{Oil Price} + 0.540 * \textit{US PMI} + 0.391 * \textit{EC Capacity} - 0.382 * \textit{China PMI} + 0.261 * \textit{Exchange Rate} \quad (5)$$

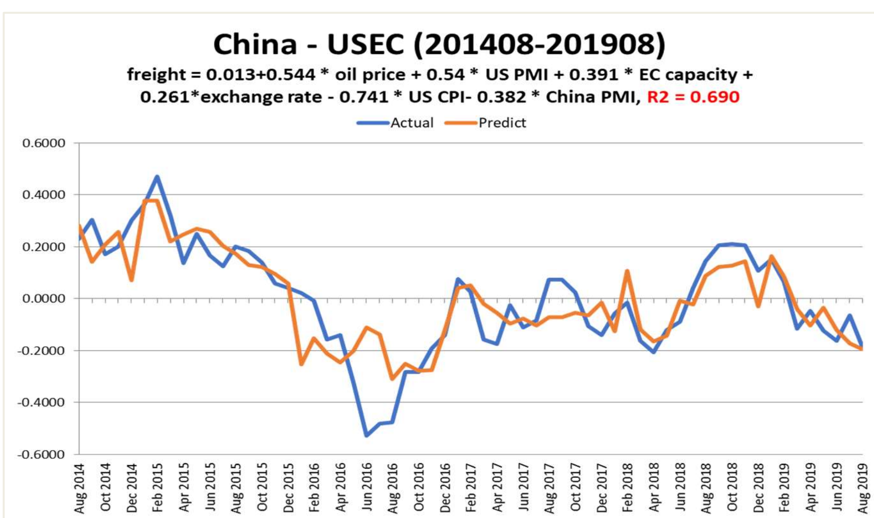



*Figure 6: China – USEC ocean freight spot rate (August 2014 – August 2019)*
*Prediction vs. Actuals*

*4.1.3.1. Critical Parameters for the China – USEC Spot Rate*

Through stepwise regression, we find that all the parameters entering the model play a significant role in determining the China – USEC ocean freight spot rate. Table 7 ranks the influence of the parameters; that is, how much the China – USEC spot rate will move if a particular economic indicator changes by one unit while the rest of the indicators remain constant. It is represented by the absolute value of the linear coefficient (β). According to Table 7, the top three critical parameters influencing the China – USEC spot rates are US CPI, oil price and US PMI.

*Table 7: Rank of the influence of the indicators over the China –USEC spot rate*

| Rank | Parameters | Coefficients ($\beta_i$) |
|---|---|---|
| 1 | US CPI | $\beta_1 = -0.741$ |
| 2 | Oil Price | $\beta_2 = 0.544$ |
| 3 | US PMI | $\beta_3 = 0.540$ |
| 4 | EC capacity | $\beta_4 = 0.391$ |
| 5 | China PMI | $\beta_5 = -0.382$ |
| 6 | Exchange rate | $\beta_6 = 0.261$ |

The coefficients β of the US CPI and the China PMI are negative, indicating that when the US CPI or the China PMI increases, it will depress the China – USEC spot rate. The coefficients β of all the other parameters are positive, meaning that when they increase, the China – USEC spot rate will also increase.

*4.1.3.2. China – USEC Model Evaluation*

**1) China – USEC Model Parameters**

- $R^2 = 0.690$

The six indicators in the stepwise regression model can explain 69% of the variances in the actual USEC spot rate ($R^2$ =0.690), the best result among all the predictive models in this research.

- Variance Inflection Factor (VIF)

The VIFs of all the regression coefficients β are around 1 – 4, safely within the range of 0.1 to 10. This means that the multicollinearity of β in this model is within the tolerance. Therefore, the model has minimized the bias resulting from the strong correlations among parameters.

- The significance of the β coefficients

The significance of the β coefficients is defined as the p-value derived from the 2-tail hypothesis test (UCLA, 2020). In this research, if the significance of all the β coefficients is within 0.05, then they are statistically significant. For the China – USEC model, the significance of all the β coefficients are well below 0.05 (all at 0.000 except for the β coefficient of the currency exchange rate, which has a significance of 0.016). Hence, all the β coefficients are statistically significant.

**2) China – USEC Model Outcomes: Prediction vs. Actuals**

Figure 6 shows that the predicted values capture not only the general trends but also the impact of a few events. For example, the model identifies a surge in the freight rate from August to December 2018. In reality, the surge was stimulated by the US – China tariff war, which started in July 2018 (Tan, 2018). The effect of the US – China tariff war on the ocean freight market is discussed in detail in Section 5.4.2.

### 4.1.4. A Predictive Model for the China – USWC Spot Freight Rate

The stepwise regression model for China – USWC spot rate returns an $R^2$ of 0.244 (Appendix C), which is significantly worse than the China – USEC accuracy ($R^2$ = 0.690). To improve the model, we adopted the standard regression which forces all the features to be included in the model, hoping to achieve a better result. Equation 6 presents the formula from the standard regression and Figure 7 visualizes the China – USWC predicted rate versus the actual rate from CHR.

$$\textit{China-USWC Spot Freight Rate} = 0.021 + 1.010 * \textit{Oil Price} + 0.712 * \textit{Exchange Rate} - 0.680 * \textit{US CPI} + 0.539 * \textit{US PMI} + 0.571 * \textit{China PM} \quad (6)$$

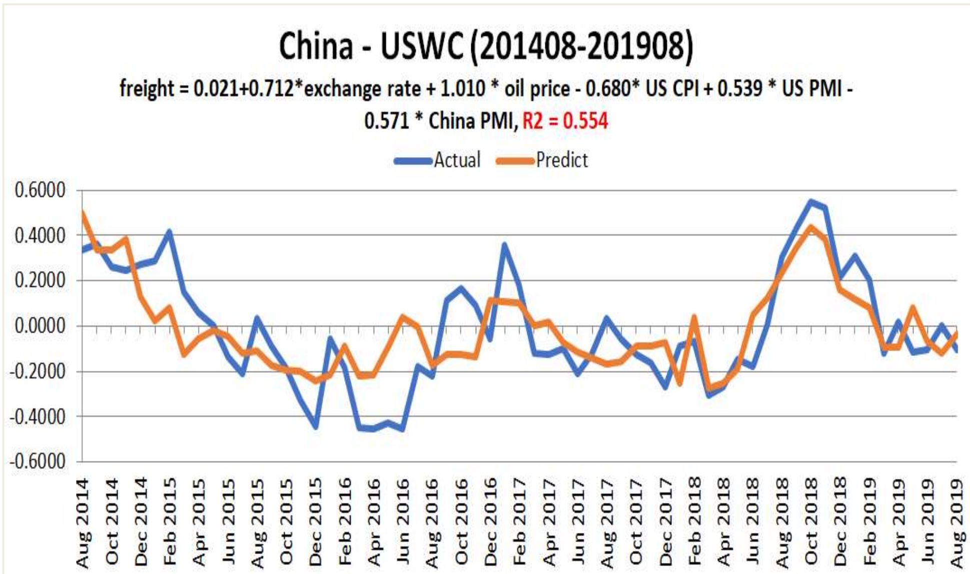



*Figure 7: China – USWC ocean freight spot rate (August 2014 – August 2019)*
*Prediction vs. Actuals*

The standard regression model improves the $R^2$ to 0.554, slightly lower than that of the China – USEC model, but much better than the stepwise regression result. In the next two subsections, we discuss the critical parameters affecting the China – USWC spot rate and evaluate the model.

#### *4.1.4.1. Critical Parameters for the China – USWC Spot Rate*

In the initial standard regression model, the US CPI displays a VIF of 12.695, greater than 10, and WC shipping capacity has a VIF of 8.703, very close to 10. To avoid the bias introduced by multicollinearity among the features, we had to remove one of the two indicators. As the WC shipping capacity data were only available on an annual level — which could be less informative than the monthly US CPI data — we moved the WC shipping capacity.

Table 8 shows how we predict the China – USWC spot rate to change with one-unit of change in each economic indicator. The top three critical indicators are oil price, exchange rate and the US CPI. As the US CPI and the China PMI have negative β, we predict that increase in these two parameters will lead to a drop in the China – USWC spot rate. For the rest of the indicators having positive β, their increase will raise the USWC spot rate.

*Table 8: Rank of the influence of the indicators over the China – USWC spot rate*

| Rank | Parameters | Coefficients ($\beta_i$) |
|---|---|---|
| 1 | Oil Price | $\beta_1 = 1.010$ |
| 2 | Exchange rate | $\beta_2 = 0.712$ |
| 3 | US CPI | $\beta_3 = -0.680$ |
| 4 | US PMI | $\beta_4 = 0.539$ |
| 5 | China PMI | $\beta_5 = -0.571$ |

*4.1.4.2. China – USWC Model Evaluation*

**1) China – USWC Model Parameters and Improvement**

- $R^2 = 0.554$

$R^2$ of the USWC enter regression model is 0.554, meaning that the five indicators can explain 54% of the variances in the actual China – USWC spot rate.

As mentioned, the $R^2$ is slightly lower than that of the USEC stepwise regression ($R^2 = 0.690$), but it has significantly improved from the China – USWC stepwise regression (Appendix C), which identifies oil price as the only significant parameter and derives an $R^2$ of 0.244.

- Variance Inflection Factor (VIF)

After removing the WC capacity, we reduced the VIF for US CPI from 12.695 to 3.014 and the rest of the parameters all display a VIF between 2 and 3, well within the range of 0.1 to 10. Hence, all the parameters are considered independent in the standard regression.

- The significance of the β coefficients

The significance of all the β coefficients is close to 0.000, well below 0.05. Hence, all the β coefficients are statistically significant.

**2) China – USWC Model Outcomes: Prediction vs. Actuals**

Figure 7 in Section 4.1.4 shows that similar to the China – USEC model, the China – USWC regression model is able to capture the general trends and the major surges in the spot rates. However, the model overall performs worse than the USEC model in capturing the extreme values, especially those before the first half of 2017. Such situation might be improved by incorporating relevant new parameters into the model, or by exploring other predictive models (e.g. non-linear regression).

### 4.1.5. Comparing the Prediction for China – USEC and China – USWC Spot Rates

*4.1.5.1 Similarities*

After removing the US GDP, China GDP and the WC capacity, which are strongly correlated with US CPI, we discover that each of the remaining indicators, including the oil price, US CPI, currency exchange rate, US PMI, China PMI and EC shipping capacity, play a critical role in predicting the China – US spot ocean freight rates, both for USEC and USWC.

Oil price is among the top three critical indicators for both the USEC and USWC spot rates. This observation echoes the finding in Section 4.1.2 that oil price is the only parameter displaying a moderate correlation with both the USEC and the USWC spot rates, while most of the other parameters are weakly correlated to at least one of spot rates.

Another similarity is that all the indicators influence USEC and USWC spot rates in the same direction. In both models, only US CPI and China PMI display negative β, indicating a depressing effect on the spot rates when they increase. The remaining parameters all have positive β, meaning that their increase will raise the spot freight rates.

*4.1.5.2. Differences*

Firstly, the EC shipping capacity is independent from other features and it is significant in predicting the China – USEC spot freight rate. However, the WC shipping capacity has to be removed from the predictive model due to its strong correlation with the economic indicators such as US CPI and US GDP. Such a difference partially contributes to a distinct dynamics between the EC and WC modeling. We further discuss the differences between the EC and WC shipping capacities and their potential influence on the spot rates in Section 5.5.

Secondly, the extent of influence on the USEC and USWC spot rates is different for some parameters. Vertically, for the Chin – USEC spot rates, the top three critical parameters are: US CPI ($\beta$ = -0.741), oil price ($\beta$ = 0.544), and US PMI ($\beta$ = 0.540). However, for the China – USWC spot rates, the top three indicators are oil price ($\beta$ = 1.010), currency exchange rate ($\beta$ = 0.712) and US CPI ($\beta$ = -0.680). Horizontally, oil price and currency exchange rate have greater influence on the USWC rates ($\beta_{\text{oil price}}$ = 1.010 and $\beta_{\text{exchange rate}}$ =0.712) than the USEC rates ($\beta_{\text{oil price}}$= 0.544 and $\beta_{\text{exchange rate}}$ = 0.261), while the effects of US CPI and US PMI are similar for both the USEC and USWC rates (USEC: $\beta_{\text{US CPI}}$ = -0.741, $\beta_{\text{US PMI}}$ = 0.540, USWC: $\beta_{\text{US CPI}}$ = -0.680, $\beta_{\text{US PMI}}$ = 0.539).

Lastly, as mentioned, the stepwise regression model shows a better fit for the China – USEC lane ($R^2$ = 0.690), while it only returns an $R^2$ of 0.244 for the China – USWC lane. Even after changing to the standard regression to include more features, the USWC model still performs slightly worse than the USEC model ($R^2 = 0.554$). Such a gap indicates that the market dynamics for the USEC and USWC can be different. For the China – USWC lane, more factors might need to be involved, or an alternative model might be required to improve the prediction.

In summary, we are able to predict the China – USEC freight rate via a stepwise regression model with six indicators. The model explains 69.0% of the variances in the actual freight rate. For China – USWC lane, stepwise regression model predicts the freight rate poorly at an accuracy of only 24.4%. After improving the model with standard regression, we are able to predict the China – USWC freight rate with five economic indicators at an accuracy of 55.4%. In the next section, we apply the models to the SEA – US lanes.

## 4.2. The Southeast Asia (SEA) – US Lanes

To keep the prediction results comparable across the TPEB lanes, we started the SEA – US modeling with the stepwise regression, the same as what we did for the China – US lanes.

### 4.2.1. Removing the Features with Strong Correlations

Same as the China – US lanes, we performed Pearson correlation test on each SEA – US lane. Table 9 summarizes the features removed due to their multicollinearity ($r > 0.7$).

*Table 9: Features removed due to strong correlations: SEA – US lanes*

| Indicators (scaled) | Indonesia | Philippines | Singapore | Thailand | Malaysia | Vietnam |
|---|---|---|---|---|---|---|
| Currency Exchange Rate (1USD) | | | | | | |
| Oil Price | | | | | | |
| US CPI (NSA) | Removed | Removed | Removed | Removed | Removed | Removed |
| US GDP | Removed | Removed | Removed | Removed | Removed | Removed |
| Country GDP | Removed | Removed | / | | Removed | / |
| Country CPI (NSA) | | | | | | Removed |
| US PMI | | Removed | | | | |
| Country PMI | | | Removed | / | / | / |
| EC Shipping Capacity | | | | | | |
| WC Shipping Capacity | Removed | Removed | | | | |

*Slash: data not available*

We observe that both China and SEA have similar strongly correlated pairs. For most of the countries, US GDP, US CPI, the origin country GDP and the origin country CPI are highly correlated. Occasionally, other parameters such as the WC shipping capacity, the currency exchange rate, and the PMI display strong correlations and we removed them from the subsequent modeling.

### 4.2.2. The Predictive Models for SEA – USEC Spot Freight Rates

To maintain a consistent approach with the analysis for China – USEC route, we modeled the SEA – USEC spot rates via the stepwise regression. Appendix D summarizes the prediction results, covering the equations, the model accuracy ($R^2$), the visualization of the predicted spot rates against the actual CHR rates, and the ranking of the critical features. In this section, we evaluate the critical features and the $R^2$.

*4.2.2.1. Critical Parameters for the SEA – USEC Spot Rates*

Table 10 summarizes the critical economic indicators to predict the SEA – USEC spot rates, with the top three indicators for each lane and the indicators with negative coefficients specified. The table shows that the CPI of the origin country, the exchange rate, the EC shipping capacity and the oil price are the top parameters affecting the SEA – USEC spot rates. An increase in the CPI of the origin country or the exchange rate depress the USEC spot rates, while an increase in the rest of the parameters strengthen the freight rates.

However, a difference between SEA – USEC and China – USEC lanes is that for SEA – USEC lanes, not all six indicators were found significant to the USEC spot rates. Table 10 shows that most of the lanes have only 1 to 3 significant indicators.

*Table 10: Rank of the influence of the indicators over the SEA – USEC spot rates*

| Indicators (scaled) | Indonesia | Philippines | Singapore | Thailand | Malaysia | Vietnam |
|---|---|---|---|---|---|---|
| Exchange Rate | 2 | 2 (-) | NA | NA | NA | 1 (-, SGN) |
| Oil Price | 3 | NA | NA | 1 | 2(PKG), 1(TPP) | |
| US CPI (NSA) | Removed | Removed | Removed | Removed | Removed | Removed |
| US GDP | Removed | Removed | Removed | Removed | Removed | Removed |
| Country GDP | Removed | Removed | | NA | Removed | |
| Country CPI (NSA) | 1 (-) | NA | 1 | 2(-) | 3 (-,TPP) | Removed |
| US PMI | | Removed | NA | NA | NA | 1 (TOT) |
| Country PMI | | NA | Removed | | | |
| EC Shipping Capacity | | 1 | NA | 3 | 1 (PKG), 2 (TPP) | 2 (SGN) |
| Number of Critical Parameters | 6 | 2 | 1 | 3 | 2 (PKG), 3 (TPP) | 2 (SGN), 1 (TOT) |

*Numbers: rank of importance; (-): negative β; NA: excluded by the stepwise regression;*

*Removed: removed due to strong multicollinearity; slash: data not available*

#### *4.2.2.2. SEA – USEC Model Evaluation*

- $R^2$

The $R^2$ of all the SEA – US models are summarized in Table 11.

*Table 11: R2 of SEA – US spot ocean freight rates mode*

| Country | USEC (stepwise) | USWC (stepwise) | USWC (standard) |
|---|---|---|---|
| Indonesia | 0.680 | 0.243 | 0.314 |
| The Philippines | 0.430 | 0.127 | 0.062 |
| Singapore | 0.138 | 0.291 | NA |
| Thailand | 0.484 | 0.246 | 0.251 |
| Malaysia - PKG | 0.371 | 0.266 | 0.266 |
| Malaysia - TPP | 0.694 | 0.273 | 0.291 |
| Vietnam - SGN | 0.461 | 0.250 | 0.109 |
| Vietnam - TOT | 0.394 | 0.210 | 0.145 |

The models for Indonesia and the Malaysia TPP port achieve a comparable performance with the China – USEC model ($R^2$ = 0.680 and 0.694 respectively). It is worth noticing that instead of involving all six indicators, the model for Malaysia TPP – USEC only includes three indicators, namely oil price, the EC shipping capacity, and the Malaysia CPI. Yet, the three indicators are able to explain 69.4% of the variances in the Malaysia TPP – USEC spot freight rate.

For the rest of the lanes, $R^2$ is around 0.3 to 0.4. For Singapore – USEC, $R^2$ is only 0.138. The low $R^2$ might attribute to:

1) Data availability: As shown in Table 10, the data for a few parameters were not available or only available over a short period of time in certain countries. The difficulties in collecting a considerably comprehensive set of data reduce the amount of information that can be included in the model for a better prediction;
2) There could be other parameters affecting the SEA ocean freight rates and have not been included in the model; and
3) Stepwise regression might not be an effective model for the SEA prediction.

- VIF and the significance of the coefficients β

All the parameters involved in the SEA – USEC model are independent (VIF within 0.1 to 10) and the coefficients β are significant (i.e., coefficient significance < 0.5).

### 4.2.3. The Predictive Models for SEA – USWC Spot Freight Rates

Appendix E displays the outcomes of the SEA – USWC stepwise models. Similar to the China – USWC prediction, the stepwise regression does not work well for the SEA –USWC prediction (Table 11). The $R^2$ is only at around 0.2 to 0.3. The critical indicators identified for most of the lanes is only oil price, which is also similar to the outcome of the China-USWC stepwise regression model (Appendix C).

However, unlike the China – USWC model, the performance for SEA-USWC models could not be improved by the standard regression. The standard regression returns similar or even poorer $R^2$. Besides, the significance of the coefficients β is largely beyond 0.05, indicating that the equations derived from the standard regression are not reliable. A potential explanation is that the input parameters for the SEA – USWC standard regression are from the SEA – USEC stepwise regression, because we assumed that the parameters explaining the USEC dynamics would be the key factors influencing the USWC dynamics as well. Nonetheless, compared with the indicators identified in the China – USEC stepwise regression model, those identified in the SEA – USEC stepwise regression model are less effective in explaining the dynamics ($R2_{China\ –\ USEC} = 0.690$ while $R2_{SEA-USEC}$ ranges around 0.3 and 0.4). Therefore, similar to the discussion on the SEA – USEC models, better data availability or an alternative model might help to improve the prediction.

This section presents that the accuracy of stepwise regression model for SEA – USEC spot rates vary from 13.8% to 69.4%. The SEA – USWC model performs more poorly at a prediction accuracy of 20% – 30%, and such performance can hardly be improved via standard regression. The limited data availability could be a reason for the diminished results compared to the China – US models.

# Chapter 5. Managerial Insights for the China – US Lanes

We have identified the economic indicators affecting the TPEB ocean freight spot rates and built MLR models to predict the rates. We have also explored the dynamics between each indicator and the spot freight rates via Pearson correlation analysis. In this section, we will explain the research findings in a commercial context to advance our understanding about the TPEB ocean freight spot market. To ensure an in-depth analysis, we focus only on the China – US lanes, which occupied 63% of the total trade volumes on the TPEB lanes in 2019 (Figure 2, Section 1.2).

## 5.1. The Influence of Each Economic Indicator: Discussion in a Commercial Context

Through interpreting the correlations between individual parameters and the ocean freight rates in a commercial context, we aim to help the industrial professionals understand how each economic indicator in this research might interact with the China – US ocean freight rates.

### 5.1.1. Oil Price and Bunker Fuel Cost

As highlighted in Section 4.1.2, oil price is the only parameter moderately correlated with both the USEC ($r = 0.335$) and the USWC ($r = 0.494$) spot rates, while the rest of the parameters are only moderately correlated with one of them or weakly correlated with both.

A separated correlation test (Appendix F) suggested that oil price has a strong positive correlation with the bunker fuel cost ($r = 0.7$), which means that the higher the oil price is, the higher the bunker fuel cost will be. This corresponds to the fact that a freight contract typically includes a term called Bunker Adjustment Factor (BAF) (iContainers, 2017), which is a surcharge that compensate the ship owners for the fluctuations in bunker fuel cost.

Hence, it is not surprising that the oil price, by influencing the bunker fuel cost, has a positive and considerably significant correlation with the spot freight rates.

### 5.1.2. Currency Exchange Rate (CNY – USD)

The Pearson correlation test shows that the CNY – USD exchange rate has the most significant correlation with the USEC spot freight rate among all the parameters ($r = -0.42$). In this research, we define currency exchange rate as the amount of foreign currency, in this case CNY, that 1 USD can exchange for. Therefore, the depreciation of USD is denoted by a decrease in the currency exchange rate parameter, while the appreciation of USD leads to an increase in the parameter. As a result, a negative correlation coefficient indicates that the depreciation of USD corresponds with an increase in the freight rates, while the appreciation of USD corresponds to a decrease in the freight rates.

Such a relationship is contrary to the business intuition. In a business context, the currency exchange rate is expected to be positively correlated with the ocean freight rates: Currency exchange rate influences the shipping volumes via imports and exports. A weak domestic currency suppresses imports become they become expensive. Conversely, a strong domestic currency stimulates imports become they are more economical (Kramer, 2020). Therefore, when the USD depreciates (i.e., becomes weaker), the US imports are expected to decline, leading to shrinking trade volumes and lower ocean freight rates. On the contrary, if the USD appreciates (i.e., becomes stronger), the US market will be incentivized to import more, generating higher trade volumes on the China – US lanes and thus increasing the ocean freight rates.

Two potential explanations for the conflicts are:

1) Other parameters might have exerted greater influence on the freight rates than the exchange rate did. The plot for currency exchange rate and China – USEC spot rate (Figure 4 in Section

4.1.2.1) shows that the relatively opposite movement was particularly explicit from May 2015 to May 2016. The demand and supply statistics (Figure 3 in Section 2.1.1) displays that during 2015 and 2016, the entire US shipping market was experiencing extremely sluggish demand growth, which may have led to a sharp decline in the spot rates. Hence, the effect of the currency exchange rate may have been offset by the more significant drop in demand.

2) To protect the shipping service providers from the exchange rate fluctuation, there is often a Currency Adjustment Factor (CAF) in the freight contract to compensate for any existing exchange rate risks (iContainers, 2017). Therefore, the intuitive impact of the exchange rate on the ocean freight rate might have been hedged by the CAF.

### 5.1.3. Purchasing Managers' Index (PMI)

PMI is a prevailing economic indicator for the manufacturing sector, representing the economic outlook in a purchasing manager's point of view (Chappelow, 2020a). For the US market, a PMI above 50 suggests an economic growth, while a PMI below 50 suggests contraction (Li, 2019). PMI is affected by purchasing managers' confidence in the economy, the outlook for imports and exports, and operational indicators such as the amount of inventories, new orders, and backlogs (Picardo, 2019). Such a business context indicates that PMI strengthens the ocean freight rates when it increases: A large US PMI stimulates the manufacturing activities, demand of goods, and imports, hence increasing the demand for logistics services.

The correlation analysis in this research shows that the US PMI is moderately and positively correlated with the China – USWC spot freight rate ($r = 0.346$), supporting the business interpretations above. However, the rest of the correlations, including the US PMI vs. the China – USEC rates and China PMI vs. both USEC and USWC rates, are very weak ($r = 0$ to $0.2$). This result suggests that the interaction between PMI and ocean freight rates is not explicit or significant.

### 5.1.4. Shipping Capacity

We find that the EC shipping capacity, following the currency exchange rate and the oil price, is the third most correlated indicator with the China – USEC freight rate (r = 0.322). However, as discussed in Section 4.1.2, the fact that the data on the shipping capacity were only available at an annual level makes it difficult to examine its impact on the freight rates in greater depth. Therefore, more efforts might be required to improve the data availability and tractability on the shipping capacity fluctuation.

Another interesting observation is that while EC shipping capacity moderately correlates with the China – USEC spot rate, the WC shipping capacity has almost no correlation with the China – USWC spot rate (r = 0.129). We discuss the differences between the EC and WC shipping capacities in detail in Section 5.5.

### 5.1.5. The General Economic Indicators: US/China GDP and US/China CPI

GDP measures the monetary value of all the products and services in a country over a specific period (Chappelow, 2020b). CPI examines the average prices that consumers have to pay for a basket of goods and services. It usually reflects the cost of living and inflation (BLS, 2020). GDP and CPI are highly correlated (Table 4) and have similar correlations with the ocean freight rates: All of them are weakly correlated with the freight rates, with the coefficients r around -0.25.

The interaction between the GDP / CPI and the ocean freight rates can be complicated and two-way (Jones, 2018). On one hand, CPI and GDP influence the ocean freight rates as follows:

1) GDP and CPI together imply the real demand for products across various markets;
2) An increase in CPI indicates a higher cost of living, which may lower market demand and thus exert downward pressure on ocean freight rates; and
3) Inflation could affect the cost of fuel (Sly et. al, 2016).

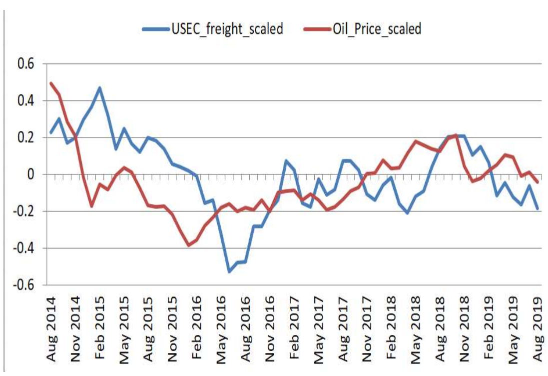
On the other hand, shipping costs contribute to the changes in GDP and CPI. If the shipping cost increases, the impact will be passed down to consumers after 6 months to 1 year and thus increases the CPI.

Therefore, although the initial analysis indicates a weak correlation between the GDP/CPI and the ocean freight rates, their influence on the ocean freight market could be sophisticated.

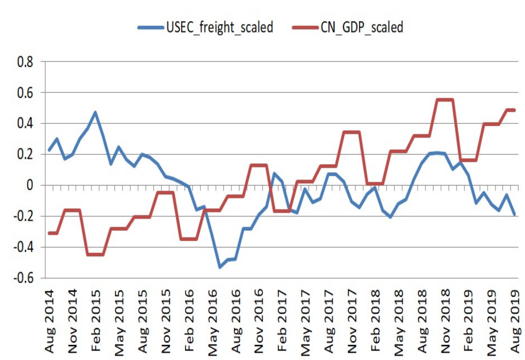
## 5.2. The Promising Leading Indicators

Apart from understanding the correlations, we also examine the influence of individual indicators by exploring their leading or lagging relationship against the ocean freight rates.

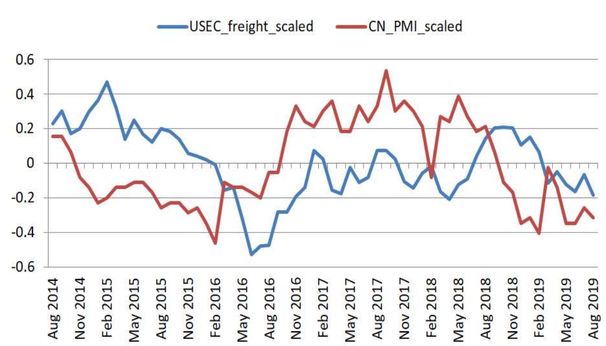
Appendix G displays the plots of each indicator against the China – US spot freight rates. We identify three indicators, namely oil price, the China GDP, and the China PMI, as the potential leading indicators for the China – USEC spot freight rate (Figure 8)




*8a: Oil price*




*8b: China GDP*




*8c: China PMI*

*Figure 8: Three potential leading indicators over the China –USEC ocean freight spot rate*

Based on the general parallelism of the two lines in Figure 8, we estimate that the oil price leads the China – USEC spot rate by 3 months, the China GDP leads the China – USEC spot rate by 1 – 3 months, and the China PMI leads the China – USEC spot rate by 3 months.

However, we cannot find any lagging indicators against the China – USEC spot rate. We also cannot identify any leading or lagging indicators against the China – USWC spot rate.

We would also like to highlight that a rigorous statistical analysis should be developed to verify the leading or lagging effects observed above.

## 5.3. The Integrated Effects of Multiple Economic Indicators on the Spot Freight Rates

Moving beyond understanding the effect of each indicator in China – US spot rates, in this section, we interpret the predictive models within a business context in order to unveil the integrated dynamics of multiple critical indicators.

### 5.3.1. Understanding China – USEC Modeling Results in a Commercial Context

According to the stepwise regression model for the China – USEC ocean freight rate (Section 4.1.3), we can rank the critical economic indicators and their effects on the China – USEC freight rate as: US CPI (negative) > oil price (positive) > US PMI (positive) > EC shipping capacity (positive) > China PMI (negative) > currency exchange rate (positive).

Below elaborates the effects of each parameter in a business context:

1) **US CPI (with negative β):** According to the predictive model, US CPI has the greatest absolute value of β, but the sign of β is negative. This means that US CPI exerts the greatest downward pressure on the China – USEC ocean freight rate. An increase in CPI, which might imply higher inflation or a greater cost of living (Section 5.1.5), will weaken the China – USEC spot rate, while a decrease in CPI will strengthen the rate.

2) **Oil price (with positive β):** Aligned with the analysis on individual parameter in Section 5.1.1, a higher oil price leads to higher China – USEC spot rate, most likely because of the higher bunker fuel cost.

3) **US PMI (with positive β):** The US PMI strengthens the China – USEC spot rate when it increases, indicating, according to Section 5.1.3, a promising economic outlook on the manufacturing industry from the purchasing managers' perspective. On the contrary, when the US PMI drops, the purchasing managers are pessimistic about the economy, and the China – USEC spot freight rate will drop.

4) **EC shipping capacity (with positive β):** Greater shipping capacity on the East Coast positively contributes to the spot rates. The more shipping capacity available for the EC, the higher the spot rates will be.

**5) China PMI (with negative β):** The negative β indicates that China PMI suppresses the USEC spot rates. When purchasing managers are positive about the economic outlook of the manufacturing industry in China, the China – USEC spot rate will drop slightly.

6) **Currency exchange rate (with positive β):** In the predictive model, the currency exchange rate supports the China – USEC spot rate: When the USD appreciates against CNY (i.e., currency exchange rate parameter defined in this research increases), the China – USEC spot rate will increase. This is in line with Chi's (2016) research as reviewed in Section 2.1.1. It also echoes the business context analyzed in Section 5.1.2 that the appreciation of the USD would stimulate imports and thus increases the ocean freight rates. Another note is that the exchange rate has the least contribution to the China –USEC spot rate (i.e., the smallest absolute value of β) among all the 6 parameters. As explained in Section 5.1.2, this might attribute to the CAF in the freight contract, which has hedged the existing exchange rate risks.

### 5.3.2. Understanding China – USWC Modeling Results in a Commercial Context

According to the predictive model discussed in Section 4.1.4, we rank the contribution of the indicators to the China – USWC spot rate as: Oil price (positive) > exchange rate (positive) > US CPI (negative) > US PMI (positive) > China PMI (negative).

The effects of most of the parameters on the USWC rate are identical to those on the USEC rate. There are two main changes:

1) The oil price and the currency exchange rates have greater impact (i.e., larger $\beta$) on the USWC spot rate than they do on the USEC spot rate; and
*2)* Unlike the EC shipping capacity, the WC shipping capacity is not in the model because it has strong correlations with the GDP and CPI and thus it was removed to minimize bias. This difference between the EC and the WC is further discussed in Section 5.5.

Compared with separately examining the effect of each economic indicator (Section 5.1), the predictive modeling, by including the interactions among the indicators into consideration, explains the China – US ocean market dynamics and the role of each economic indicator more in line with the business reality. Such observation further verifies a general conclusion of this research that the dynamics of the ocean freight market is influenced by multiple economic indicators and the interactions among them.

## 5.4. The Disruptive Events and Their Influence on the Spot Rates

Apart from the economic indicators, a few disruptive events have once influenced or denominated the freight rate changes on the China – US lanes. Therefore, in this section, we elaborate the impact of three disruptive events, namely the Panama Canal expansion (June, 2016), the US –

China tariff war (since July, 2018), and the new maritime regulation IMO 2020, on the ocean freight market.

### 5.4.1. Panama Canal Expansion

The China – USEC ocean freight spot rate displays a drastic drop from May to August 2016 (Figure 9). A reason is that in 2016, the vessel over-supply in the global shipping market reached an extreme (Figure 3, Section 2.1.1): While shipping capacity growth hit a peak, the demand growth rate dropped from 4% – 6% to 0. The drastic over-capacity in the shipping market caused the ocean freight rates to plummet.

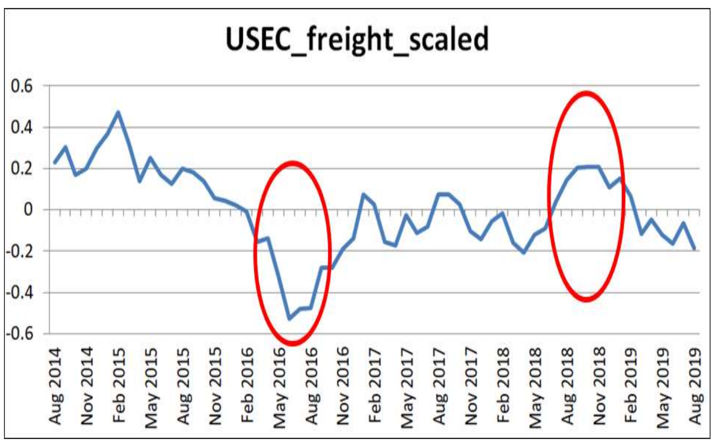



*Figure 9: The re-scaled CHR USEC spot freight rates from August 2014 to August 2019*

Another reason might be related to the Panama Canal expansion. On June 26, 2016, the Panama Canal opened its new locks and an additional shipping lane. The expansion doubled the capacity of the canal. Previously, the canal could maximally accommodate a vessel carrying 5,000 TEUs. After the expansion, a vessel carrying up to 13,000 TEUs was able to pass through (Mufson, 2016). As a result, CHR estimated that 10% to 14% of the container traffic coming into the US from Asia would be diverted to the USEC instead of the USWC (Berglund, 2016). To attract new business and obtain a competitive advantage, ship owners dropped their freight rates around the time that the expanded canal was open (Berglund, 2016).

### 5.4.2. US – China Tariff War

Another abrupt change in the ocean freight rates (Figure 9) appeared during August to December 2018. This peak was stimulated by the market's fear of the US – China tariff war. On July 6, 2018, the US implemented the first China-specific tariff increase, collecting 25% more in tariffs on 818 imported Chinese products (Wong and Koty, 2020). Since then, there have been constant threats in further increasing the tariffs on imports from China. On September 17, 2018, the US finalized another 25% tariff increase on US$200 billion of Chinese goods, effective January 1, 2019 (Wong and Koty, 2020). As a result, from August to December 2018, the US importers rushed to place orders on Chinese goods and get their cargoes to the US ports before January 1, 2019 (Tan, 2018). Consequently, the surges in demand pushed up the freight rates on China – US lanes. However, the peak soon died down to a long tail of decline in 2019 because of the prolonged battle over tariffs.

### 5.4.3. The New Industrial Regulation: International Maritime Organization (IMO) 2020 on Low Sulfur Emission

As introduced in Section 1.1, effective January 1, 2020, IMO imposed a more stringent sulfur emission cap for the shipping industry. As a result, the shipping industry had to adopt low-sulfur bunker fuels. Due to the limited supply of the low-sulfur fuel, the bunker fuel cost was expected to increase. As a result, the spot freight rates were expected to increase in 2020.

However, such expectation has not been realized in the market so far. Due to the outbreak of the coronavirus disease (COVID-19) since the beginning of 2020, the global economy has been heavily hit: The US PMI dropped to 41.5 in April 2020, indicating an economic contraction in the manufacturing industry (ISM, 2020). CHR expected that 20% – 30% of the shipping capacity would be removed from the market in response to the drastic demand decline (CHR, 2020b).

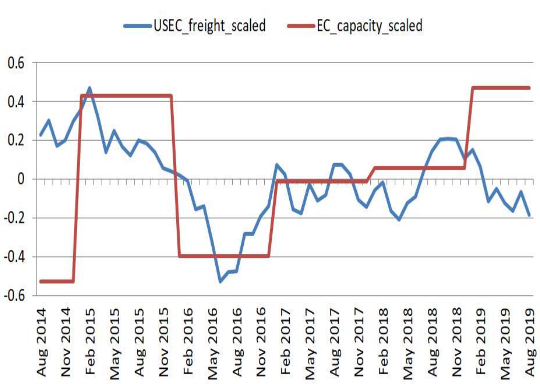
Therefore, the expected freight increase due to IMO 2020 has been offset by the collapsing market demand.

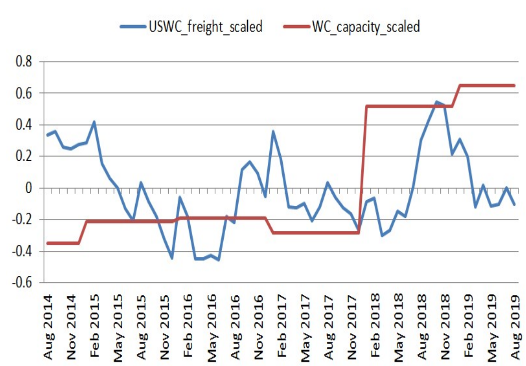
## 5.5. The Distinct Dynamics of the USWC and the USEC Spot Rates

As introduced in Section 1.1, the volumes for China – USEC routes have been rising against the traditional China – USWC routes. Besides, the predictive models also imply that there are differences in the China – USEC and China – USWC ocean freight markets, because the same economic indicators explain 69% of the variances in the USEC spot rate ($R^2 = 0.690$), but they can only explain 55% of the variances in the USWC spot rate ($R^2 = 0.554$). Two observations during this research might shed a light on the differences:

### 5.5.1. Observation 1: EC Spot Rates Are More Synchronized With the Changes in Shipping Capacity

Figure 10 compares the changes in the shipping capacities and the spot ocean freight rates for both the USEC and the USWC from August 2014 to August 2019. While EC shipping capacity moderately correlates with the China – USEC spot freight rate (r = 0.322, Table 7), the WC shipping capacity only weakly correlates with the USWC spot freight rates (r = 0.129, Table 8). The tighter correlation between the EC shipping capacity and the freight rate might have attributed to a more accurate predictive model for the EC sport frieght rate.




*10a: China – USEC spot rates and EC shipping capacity* *10b: China – USWC spot rates and WC shipping capacity*

*Figure 10: The shipping capacities and the spot freight rates (August 2014 –August 2019)*

### 5.5.2. Observation 2: WC Shipping Capacity Is More Correlated With Economic Indicators

Another observation is that the WC shipping capacity is strongly correlated with several economic indicators, including the US GDP and the US CPI, while the EC shipping capacity does not display any strong correlation with them. This difference is consistent across the TPEB lanes (Appendix H). Such strong correlation between the WC shipping capacity and the economic indicators might mean that the WC capacity is more closely adjusted according to the economic environment.

Further analysis on the difference between USEC and USWC market dynamics might help to understand the spot freight changes and good practices in the shipping industry better. However, as mentioned, a challenge is that the shipping capacity data were not readily available, especially beyond the annual frequency. Therefore, a systematic and standardized data tracking process for the shipping capacity might help to further reveal the differences in USEC and USWC market dynamics.

## 5.6. CHR Spot Freight Rates: A Proven Representative of General Market Rates

All the modeling and analysis so far have been CHR-specific. To understand whether the insights and conclusions could be generalized to the broader market, we built the predictive models with the Shanghai Containerized Freight Index (SCFI) as well. As introduced in Section 3.1.1, SCFI is a public index reporting the spot ocean freight rates for the Shanghai export container transport market.

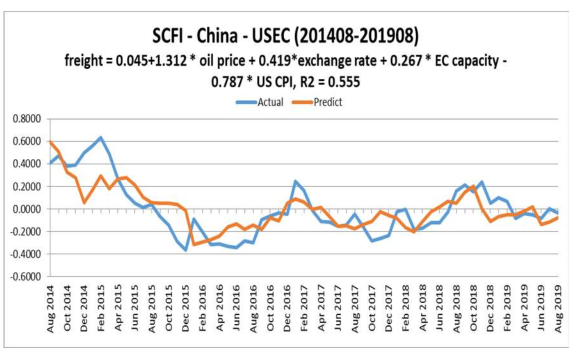
### 5.6.1. SCFI vs. CHR Spot Rates for China – USEC

Equation 7 shows the predictive formula for the SCFI China – USEC spot freight rate. Compared with the CHR China – USEC spot rate formula (Equation 5), most of the parameters have the same impact: oil price, exchange rate, and EC shipping capacity are still identified to increase the USEC spot rate as they increase (i.e., positive β), while the US CPI depresses the spot rate when it increases (i.e., negative β).

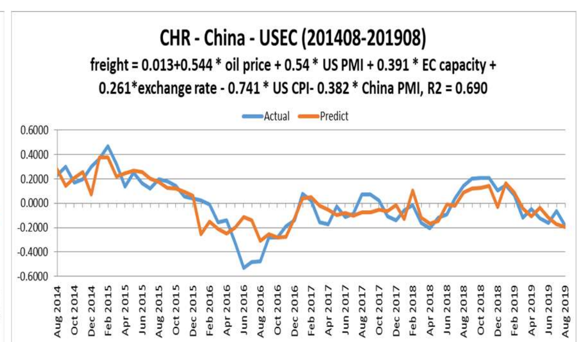
$$\textit{SCFI China – USEC Spot Freight Rate} = 0.045 + 1.312 * \textit{Oil Price} - 0.787 * \textit{US CPI} + 0.491 * \textit{Exchange Rate} + 0.267 * \textit{EC Capacity} \quad (7)$$

The only difference is that PMI was not found to play a significant role in predicting the SCFI China – USEC spot rate, while both US PMI and China PMI were identified important for the CHR spot rate prediction.

In Figure 11, the predicted SCFI China – USEC spot rate was visualized against the actuals. Meanwhile, the model was compared against that for CHR. The figure shows that the $R^2$ for the SCFI model is 0.555 (Figure 11a), slightly less than that for the CHR model (Figure 11b, $R^2$ = 0.690).




*11a: SCFI*




*11b: CHR*

*Figure 11: Comparison of SCFI and CHR spot rates modeling for China – USEC*

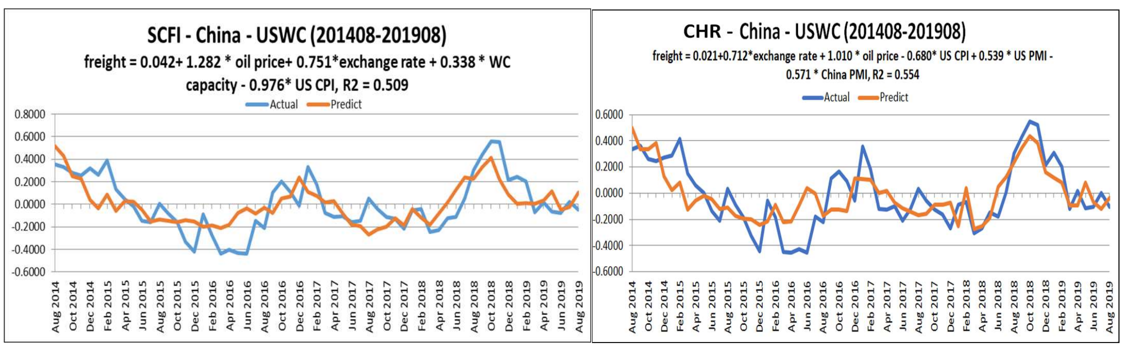
### 5.6.2. SCFI vs. CHR Spot Rates for China – USWC

A key difference between the SCFI and CHR models for the USWC spot rates is that the WC shipping capacity was found to contribute to the SCFI freight rate (Equation 8) without stimulating significant multicollinearity in the model (i.e., the VIFs for all the parameters in the

SCFI USWC model were within 0.1 to 10). Other than that, the parameters play similar roles as they do in the CHR model. To keep a consistent research approach with the CHR models, we excluded PMI from USWC modeling because they were not identified significant in the USEC model.

$$\textit{SCFI China – USWC Spot Freight Rate} = 0.042 + 1.282 * \textit{Oil Price} + 0.751 * \textit{Exchange Rate} -+ 0.338 * \textit{WC capacity} – 0.976\ \textit{US CPI} \quad (8)$$

The SCFI China – USWC spot rate prediction had an $R^2$ of 0.509 (Figure 12a), which is very close to the $R^2$ for the CHR China – USWC USWC spot rate model (Figure 12b, $R^2 = 0.554$).




*12a: SCFI* *12b: CHR*

*Figure 12: Comparison of SCFI and CHR spot rates modeling for China – USWC*

To summarize, the parameters influencing the CHR ocean freight rates play largely similar roles in the general market, apart from PMI which seemed only to be contributing to the CHR ocean freight rates. Therefore, the CHR spot rates have been proven to be representative samples of the general China – US market dynamics.

# Chapter 6. Conclusion

In this research, we leveraged the historical Transpacific Eastbound (TPEB) ocean pricing from C.H. Robinson, coupled with publicly available economic indicators and carrier data sources, in order to identify the critical economic indicators influencing the TPEB spot rates, predict the spot rates, and explore the TPEB ocean market dynamics.

We focused our analysis on the China – US routes, while we also modeled and briefly discussed the SEA – US lanes. We examined the ocean market for the US East Coast and the US West Coast separately examined due to their different freight rates and an ongoing market swing from the USWC to the USEC.

The key findings of the research are:

1) **China – USEC**: We are able to predict the China – USEC spot rate via a multiple linear stepwise regression model at 69.0% accuracy. The critical indicators identified are US CPI, oil price, US PMI, EC shipping capacity, China PMI, and currency exchange rate. When these indicators increase, the US CPI and China PMI weaken the USEC spot rate, while the rest of the indicators strengthen the USEC spot rate when they increase.
2) **China – USWC**: We predict the China – USWC spot rate via a multiple linear standard regression model at 55.4% accuracy. The critical indicators identified are largely the same as those for the USEC, except that the WC shipping capacity was removed. The effects of the indicators are also similar, but we find that oil price and exchange rate play more significant roles in the USWC market than in the USEC market.
3) The modeling results for the public spot rates (SCFI) and the CHR spot rates are largely similar, proving that CHR spot rate is a representative sample of the general China – US ocean freight spot rates.

According to above results, we recommend CHR to consider the following aspects when interpreting or predicting TPEB ocean freight spot rates in the future:

1) **Oil price and the cost of the bunker fuel**: Oil price is the most significant parameter for the TPEB spot rates because it explicitly displays great influence on both the USEC and USWC spot freight rates. The oil price is highly correlated with the bunker fuel costs. A rising oil price is likely to drive up the spot rates.
2) **US CPI**: The TPEB spot freight rates and the US CPI mutually affect each other, but the model shows that a higher CPI might depress the freight rates due to inflation and the increased cost of living.
3) **Currency exchange rate**: When the USD appreciates against the CNY, the China – US spot freight rates are likely to increase because there is greater incentive for the US to import. Conversely, when the USD depreciates, the imports might decline, leading to lower spot freight rates. However, it is worth noting that the fluctuation in the exchange rate might be partially absorbed by the currency adjustment factor (CAF) in the freight contracts.
4) **PMI**: A positive economic outlook in the manufacturing sector (i.e., an increasing PMI) is expected to increase the spot freight rates, although such influence might not be as strong as that from other indicators.
5) **Potential leading indicators**: We discover that oil price, China GDP, and China PMI potentially change 1 to 3 months ahead of the China – USEC spot freight rate. Therefore, more rigorous future analysis may focus on these 3 parameters.
6) **Disruptive events:** In the past 5 years, disruptive events or policies, such as the Panama Canal expansion, the US – China tariff war, the IMO 2020 and the COVID-19, all exerted significant impact on the freight rates.

Lastly, we would like to highlight a few potential future research directions. A key area could be the distinct dynamics between the USEC and the USWC ocean freight market. It seems that EC shipping capacity is more closely correlated with the ocean freight rate, while the WC shipping capacity is more influenced by the general market economy. Further research on the shipping capacity might be interesting, but the challenge lies in collecting and tracking the shipping capacity changes in each route. In addition, the predictive methodology could be further improved by analyzing the data at a daily, rather than monthly, level, and by exploring non-linear regression models or other advanced models to generate more accurate predictions.

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# Appendices

## Appendix A: Literature Review of Parameters

| Category | Factor | Marx (1946) | Klovland (2008) | Chi (2016) | Binkley and Harrer (1981) | Yunianto (2018) |
|---|---|---|---|---|---|---|
| Supply | Tonnage/capacity | Y | Y | | | |
| Supply | Anticipation of new ship orders | Y | Y | | | |
| Demand | Trade volumes | Y | Y | | Y | |
| Demand | Economic indicators (GDP, consumer index) | Y | Y | | | |
| Demand | Employment rate | Y | | | | |
| Demand | Currency exchange rates | | | Y | | |
| Demand | Business cycles | | Y | | | |
| Demand | Public anticipation of economic environment (consumer confidence index) | | Y | | | |

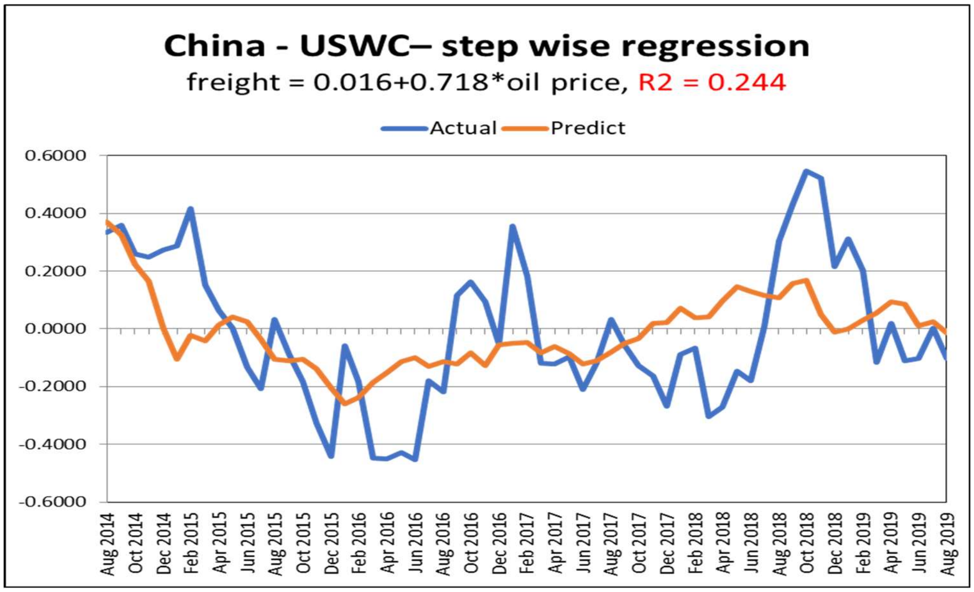
| Category | Factor | Marx (1946) | Klovland (2008) | Chi (2016) | Binkley and Harrer (1981) | Yunianto (2018) |
|---|---|---|---|---|---|---|
| Operations | Oil price | Y | | | | Y |
| Operation | Fuel price | Y | | | | Y |
| Operation | Cargo content | | | | Y | |
| Operation | Shipping distance | | | | Y | |
| Operation | Ship size | Y | | | Y | |
| Operation | Cost at port | | | | | Y |
| Disruptive events | Financial crisis | Y (war) | Y (war) | | | |
| Disruptive events | Canal expansion | Y | | | | |
| Disruptive events | Trade war | Y | | | | |
| Disruptive events | Worker strike | Y | | | | |
| Disruptive events | IMO 2020 | Y(fuel) | | | | Y(fuel) |

# Appendix B: Discussion with CHR on the Parameters to be Included in the Research

| Category | Factor | Apply to our project? | Source / Comment |
|---|---|---|---|
| Supply | Capacity | Y | From Ali's slides & Alphaliner |
| Supply | Anticipation of new ship orders | N (deprioritize) | Focus on historical data first |
| Demand | Trade volumes | Y | |
| Demand | Economic indicators (GDP, consumer index) | Y | MIT to update source |
| Demand | Employment rate | Deprioritizied | Worth to explore but at lower priority:<br>1. Drive demand<br>2. Labor for cargo movement |
| Demand | Currency exchange rates | Y | Exchange rates will change purchasing / selling patterns<br>MIT to update source |
| Demand | Macro-economic business cycles | N | 1. The project is within 10-year horizon (no sufficient data for biz cycle study which usually is only meaningful with more than 10-year data)<br>2. May consider short-term scope – seasonality etc. |
| Demand | Public anticipation of economic environment (consumer confidence index) | Y | Obtain various economic indexes (GDP, consumption index, consumer confidence index) → Understand how the indexes are calculated → explore correlations among indexes → determine which index should be kept in the model<br><br>MIT to update source |

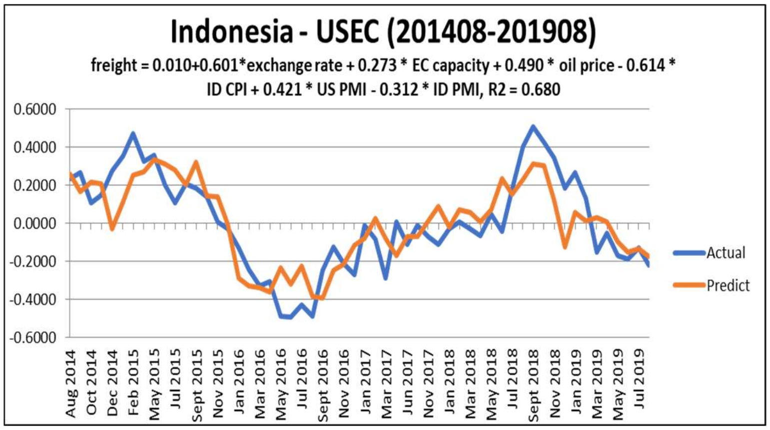

| Category | Factor | Apply to our project? | Source / Comment |
|---|---|---|---|
| Supply | Capacity | Y | From Ali's slides & Alphaliner |
| Supply | Anticipation of new ship orders | N (deprioritize) | Focus on historical data first |
| Demand | Trade volumes | Y | |
| Demand | Economic indicators (GDP, consumer index) | Y | MIT to update source |
| Demand | Employment rate | Deprioritizied | Worth to explore but at lower priority:<br>1. Drive demand<br>2. Labor for cargo movement |
| Demand | Currency exchange rates | Y | Exchange rates will change purchasing / selling patterns<br>MIT to update source |
| Demand | Macro-economic business cycles | N | 1. The project is within 10-year horizon (no sufficient data for biz cycle study which usually is only meaningful with more than 10-year data)<br>2. May consider short-term scope – seasonality etc. |
| Demand | Public anticipation of economic environment (consumer confidence index) | Y | Obtain various economic indexes (GDP, consumption index, consumer confidence index) → Understand how the indexes are calculated → explore correlations among indexes → determine which index should be kept in the model<br><br>MIT to update source |

# Appendix C: The China – USWC Stepwise Regression Model



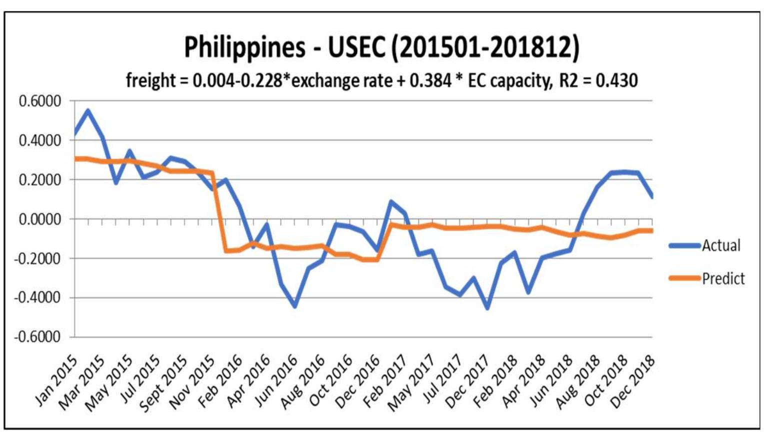
# Appendix D: SEA – USEC Stepwise Regression Models

- Indonesia – USEC



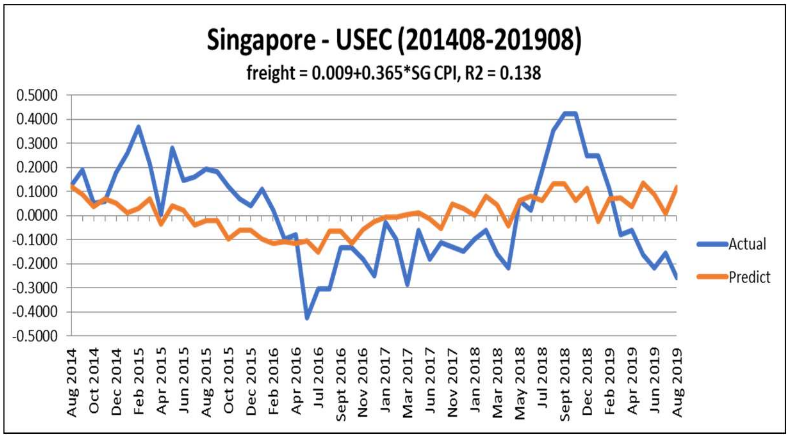

| Rank | Parameters | Coefficients |
|---|---|---|
| 1 | ID CPI | -0.614 |
| 2 | Exchange rate | 0.601 |
| 3 | Oil Price | 0.490 |
| 4 | US PMI | 0.421 |
| 5 | ID PMI | -0.312 |
| 6 | EC capacity | 0.273 |

- The Philippines – USEC



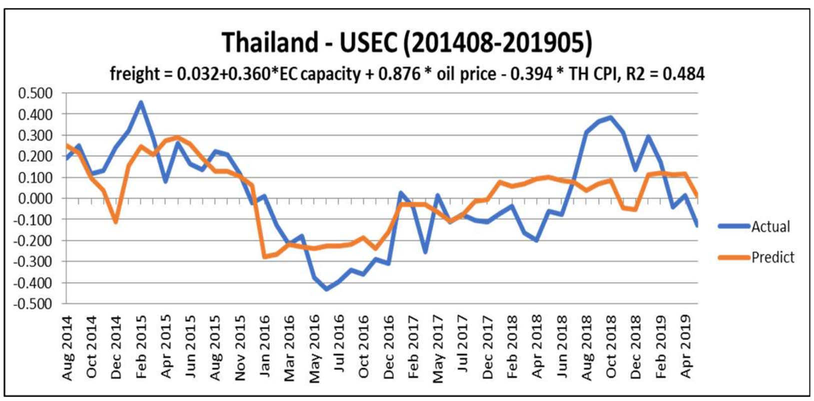

| Rank | Parameters | Coefficients |
|---|---|---|
| 1 | EC capacity | 0.384 |
| 2 | Exchange rate | -0.228 |

- Singapore – USEC



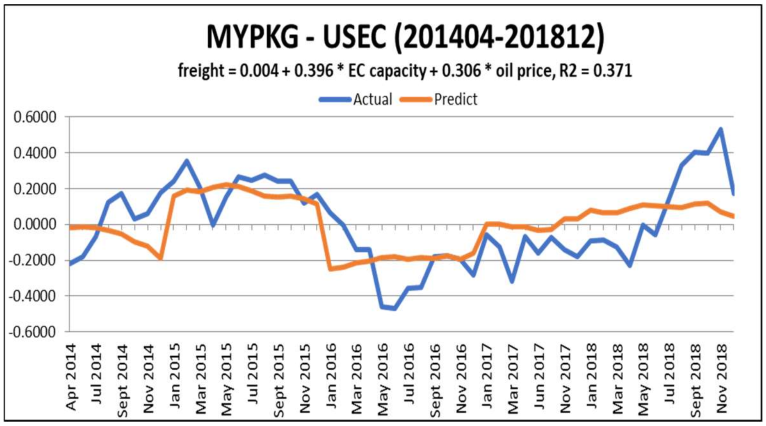

| Rank | Parameters | Coefficients |
|---|---|---|
| 1 | SG CPI | 0.3965 |

- Thailand – USEC



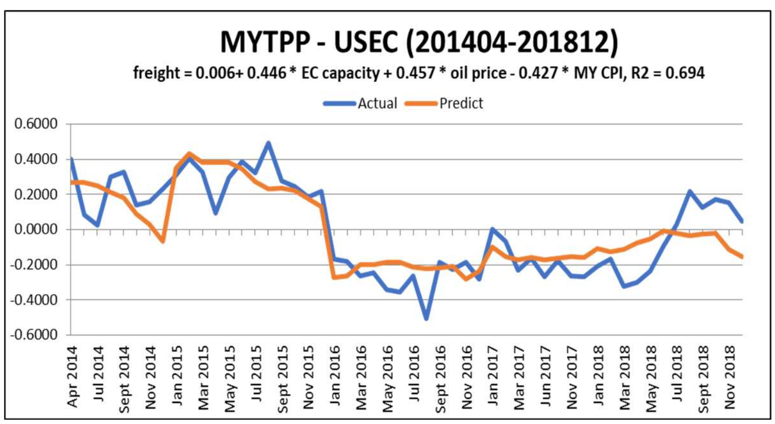

| Rank | Parameters | Coefficients |
|---|---|---|
| 1 | Oil price | 0.876 |
| 2 | TH CPI | -0.394 |
| 3 | EC capacity | 0.360 |

- Malaysia - USEC
  - PKG port – USEC



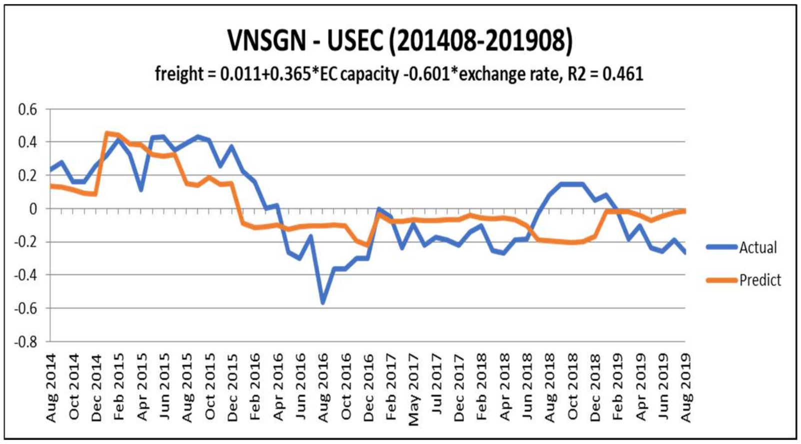

| Rank | Parameters | Coefficients |
|---|---|---|
| 1 | EC capacity | 0.396 |
| 2 | Oil Price | 0.306 |

  - TPP port – USEC



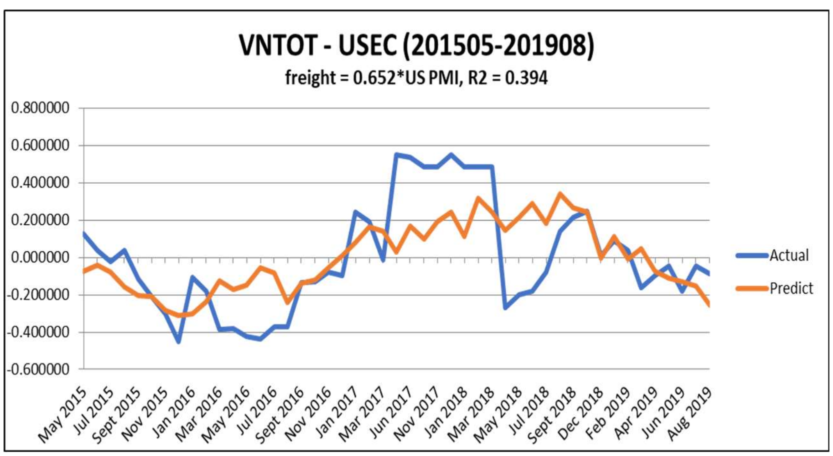

| Rank | Parameters | Coefficients |
|---|---|---|
| 1 | Oil Price | 0.457 |
| 2 | EC capacity | 0.446 |
| 3 | MY CPI | -0.427 |

- Vietnam – USEC
    - SGN port – USEC




| Rank | Parameters | Coefficients |
|---|---|---|
| 1 | Exchange rate | -0.601 |
| 2 | EC capacity | 0.365 |

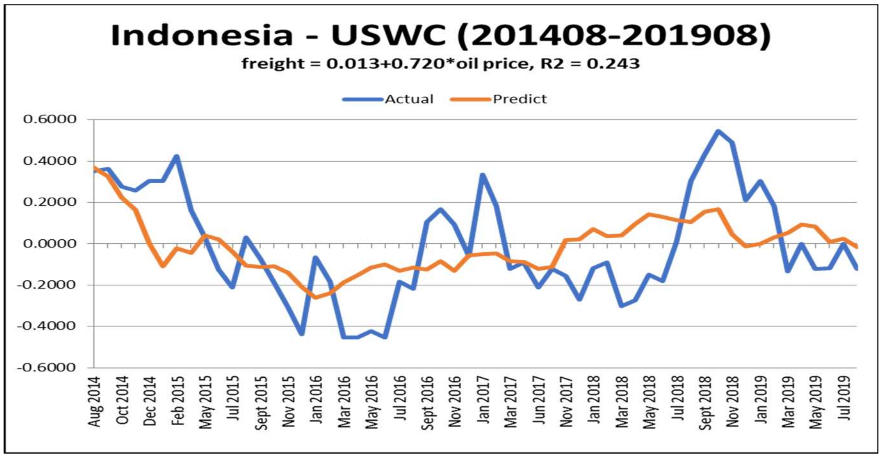
- TOT – USEC




| Rank | Parameters | Coefficients |
|---|---|---|
| 1 | US PMI | 0.652 |

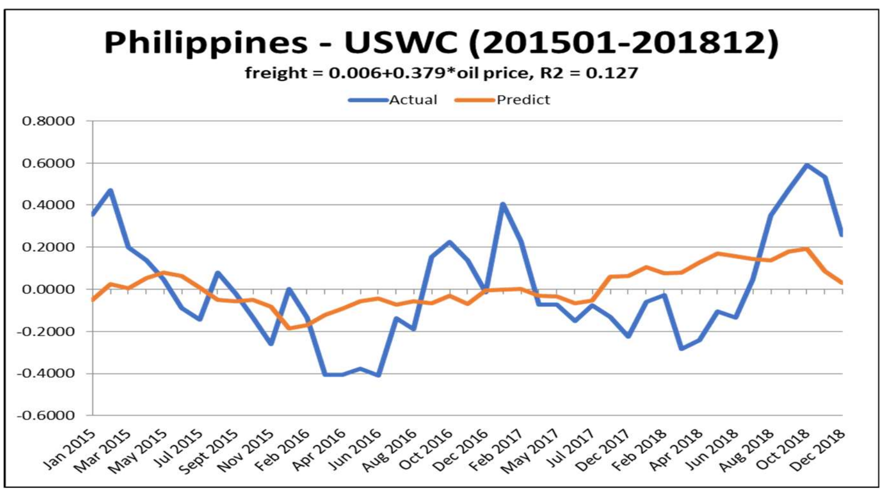
# Appendix E: SEA – USWC Stepwise Regression Models

- Indonesia – USWC



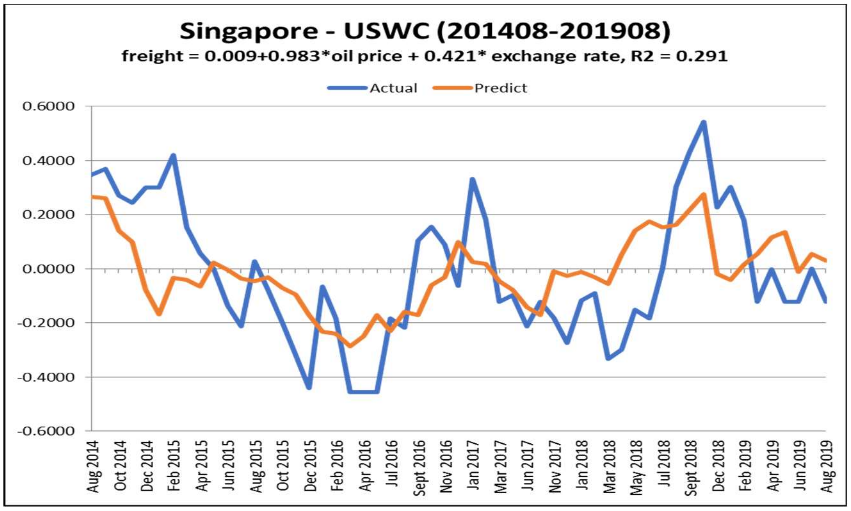

| Rank | Parameter | Coefficients |
|---|---|---|
| 1 | Oil Price | 0.720 |

- The Philippines – USWC



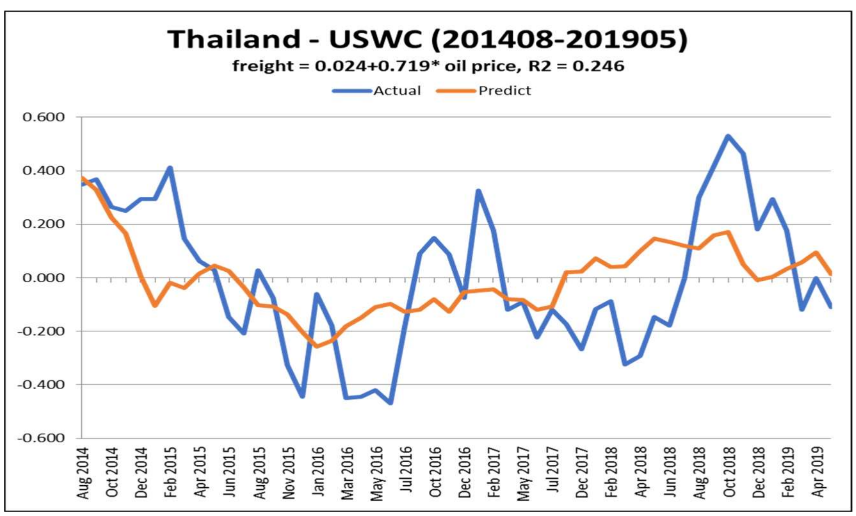

| Rank | Parameter | Coefficients |
|---|---|---|
| 1 | Oil Price | 0.379 |

• Singapore – USWC



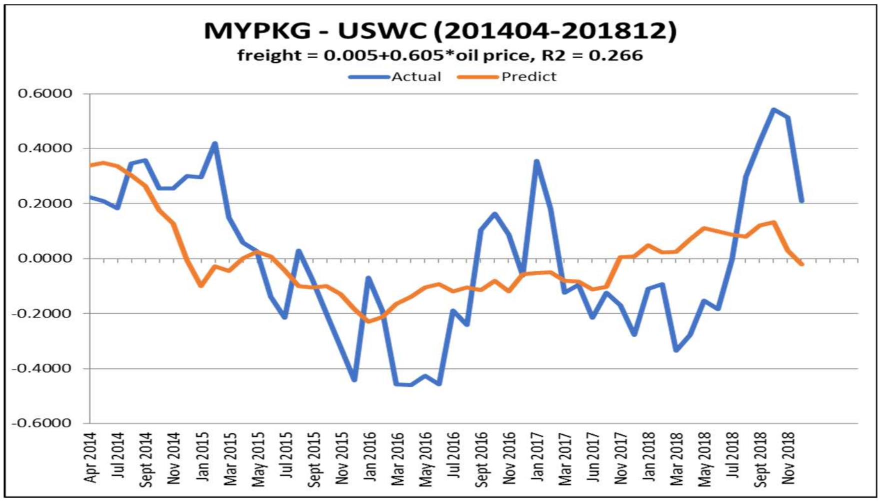

| Rank | Parameter | Coefficients |
|---|---|---|
| 1 | Oil Price | 0.983 |
| 2 | Exchange rate | 0.421 |

• Thailand – USWC



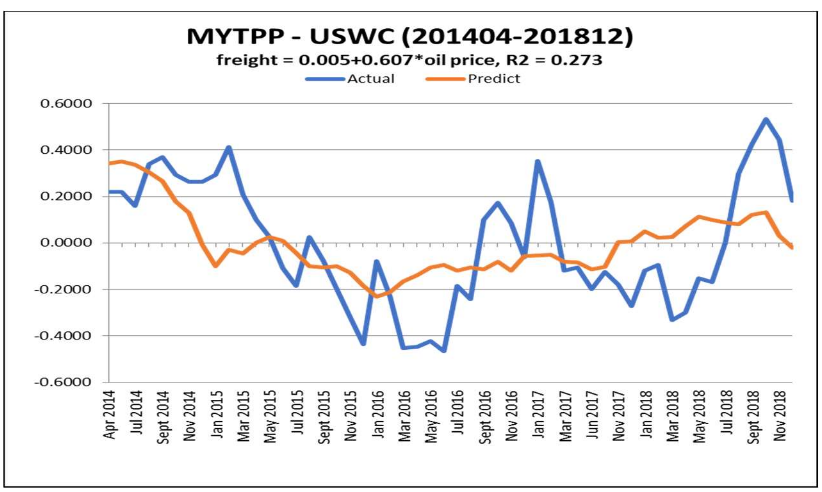

| Rank | Parameter | Coefficients |
|---|---|---|
| 1 | Oil Price | 0.719 |

- Malaysia – USWC
  - PKG port – USWC




| Rank | Parameter | Coefficients |
|---|---|---|
| 1 | Oil Price | 0.720 |

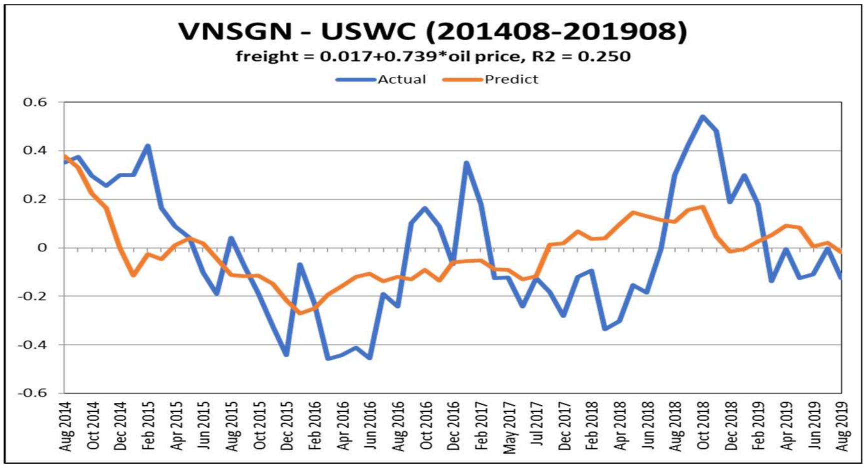
  - TPP port – USWC




| Rank | Parameter | Coefficients |
|---|---|---|
| 1 | Oil Price | 0.607 |

- Vietnam – USWC
    - SGN port – USWC

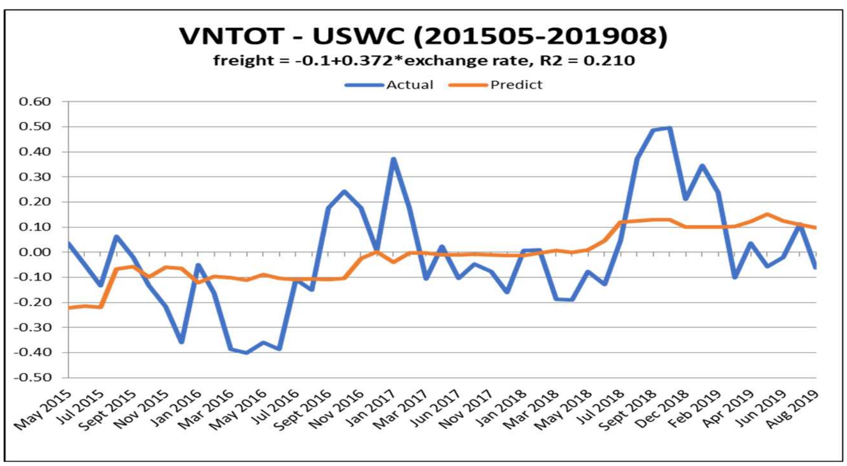
–




| Rank | Parameter | Coefficients |
|---|---|---|
| 1 | Oil Price | 0.739 |

- TOT – USWC

–




| Rank | Parameter | Coefficients |
|---|---|---|
| 1 | Exchanger rate | 0.372 |

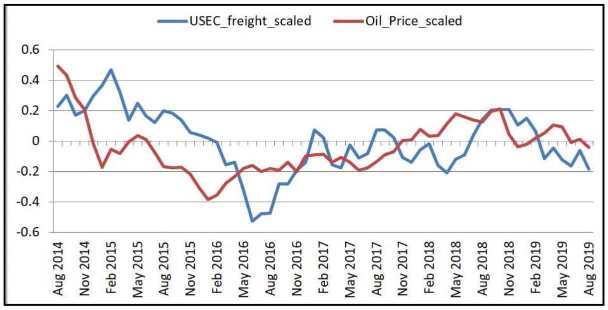
# Appendix F: Correlation between Bunker Fuel and Oil Price

```
> parameters = read.csv("Oil price consolidation.csv")
> pcor = cor(parameters[,2:3])
> pcor
          Bunker       Oil
Bunker 1.0000000 0.6928552
Oil    0.6928552 1.0000000
```

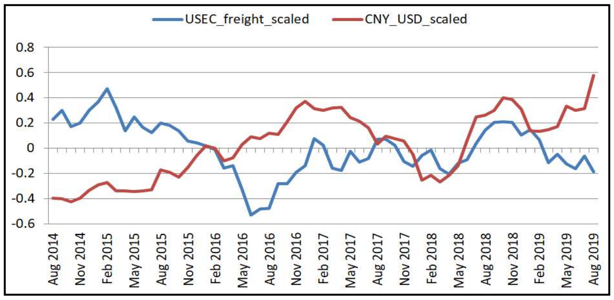
# Appendix G: Visualization of Individual Parameters vs. Ocean Freight Rates

## China – US East Coast (USEC)

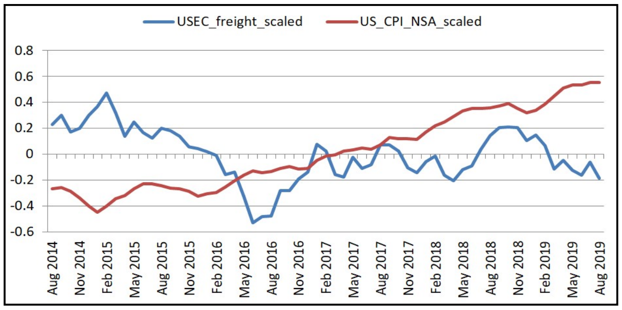
- Oil price vs. China –USEC spot ocean freight rate




- Currency exchange rate vs. China –USEC spot ocean freight rate

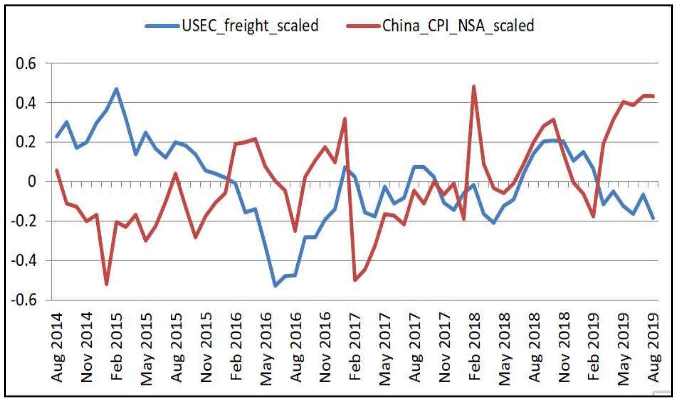



- US CPI vs. China –USEC spot ocean freight rate

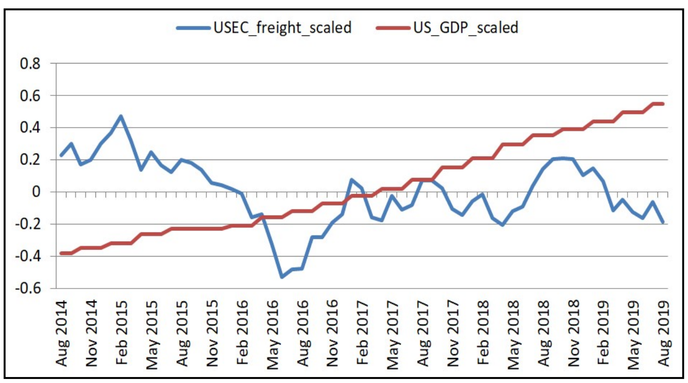


**China – US East Coast (USEC)**

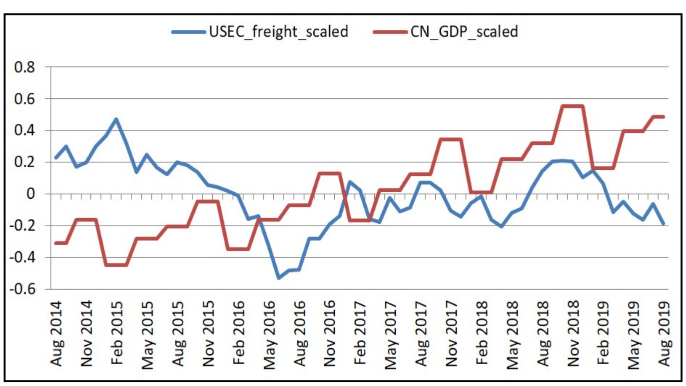
- China CPI vs. China –USEC spot ocean freight rate




- US GDP vs. China –USEC spot ocean freight rate

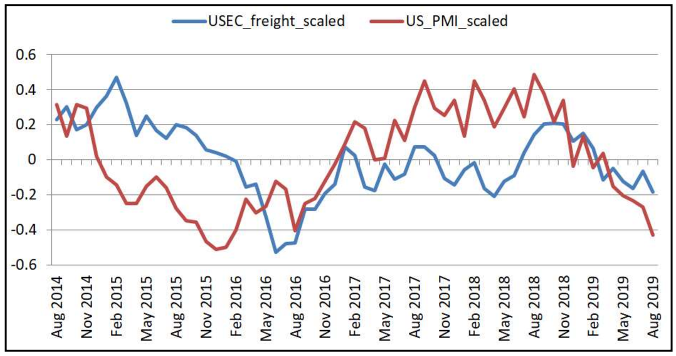



- China GDP vs. China –USEC spot ocean freight rate

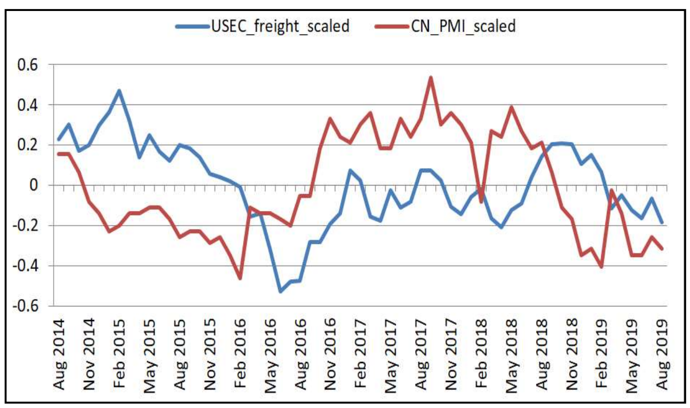


## China – US East Coast (USEC)

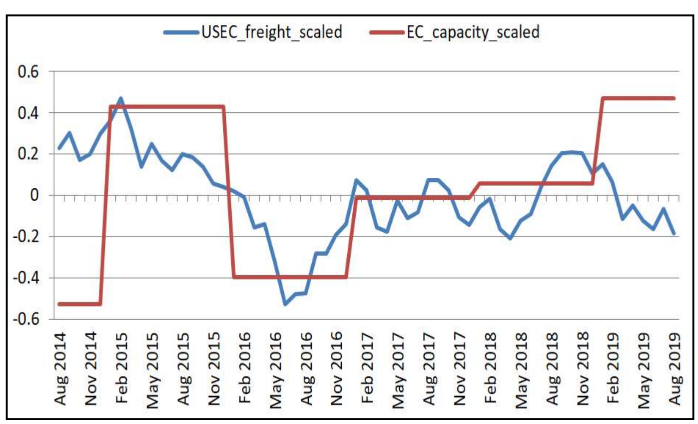
- US PMI vs. China –USEC spot ocean freight rate




- China PMI vs. China –USEC spot ocean freight rate

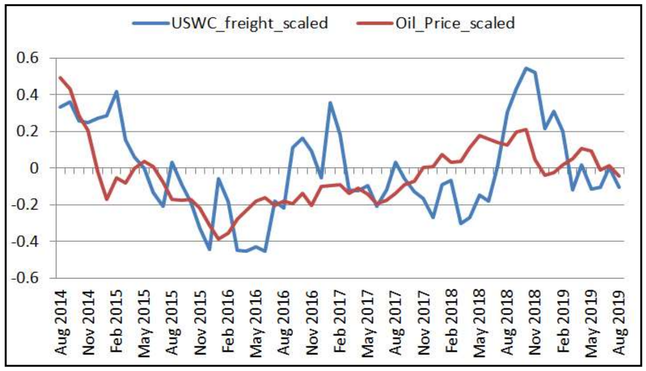



- EC shipping capacity vs. China –USEC spot ocean freight rate

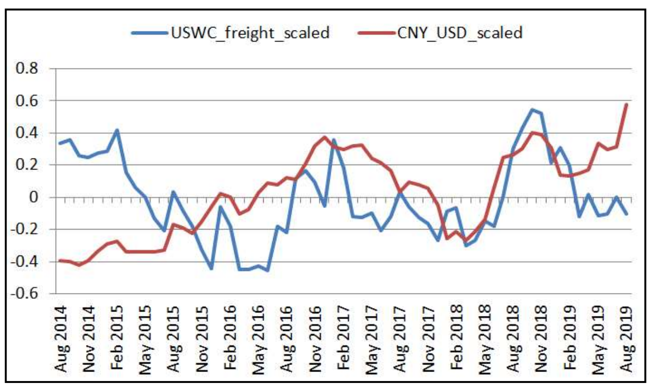


## China –US West Coast (USWC)

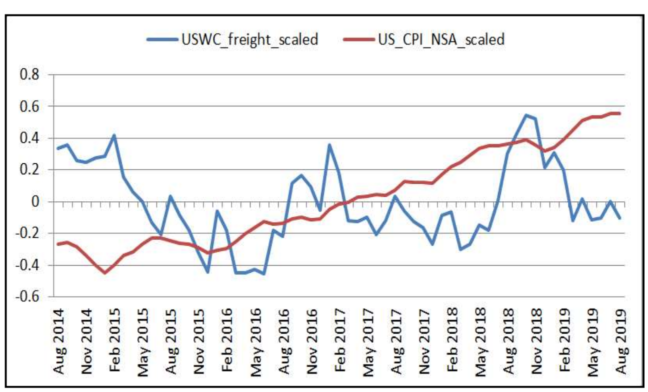
- Oil price vs. China –USWC spot ocean freight rate




- Currency exchange rate vs. China –USWC spot ocean freight rate

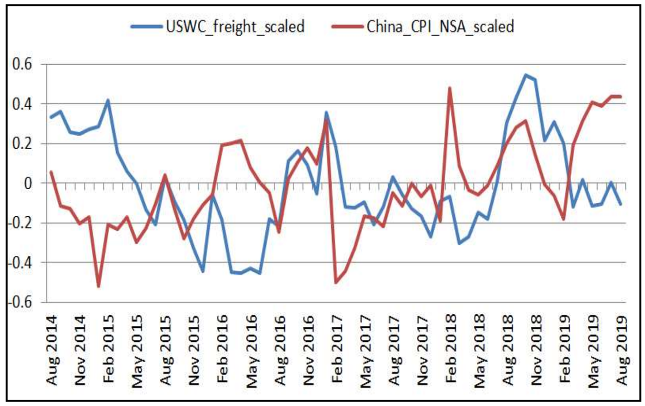



- US CPI vs. China –USWC spot ocean freight rate

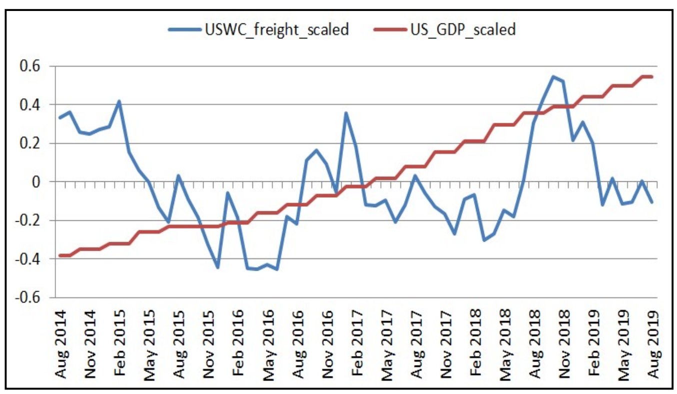


## China –US West Coast (USWC)

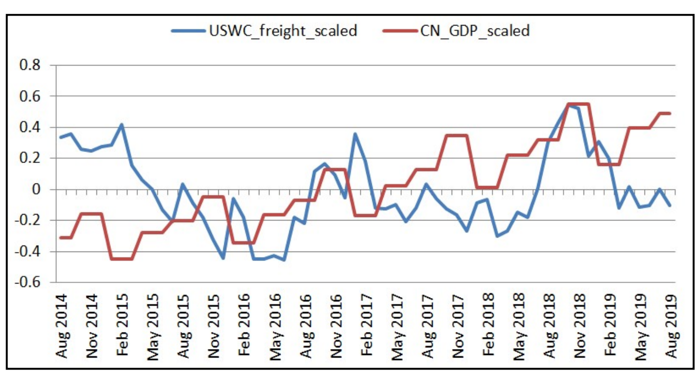
- China CPI vs. China –USWC spot ocean freight rate




- US GDP vs. China –USWC spot ocean freight rate

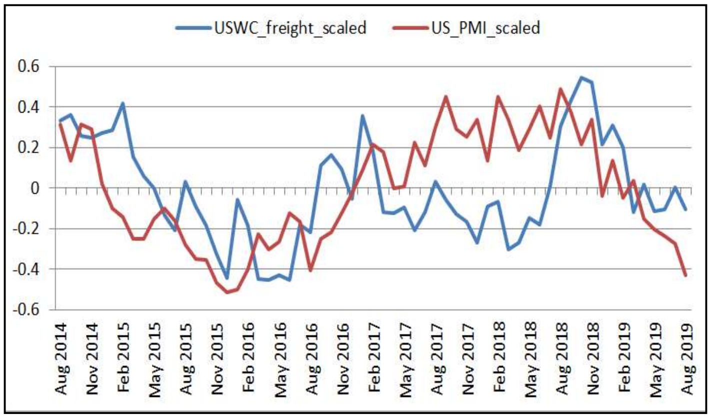



- China GDP vs. China –USWC spot ocean freight rate

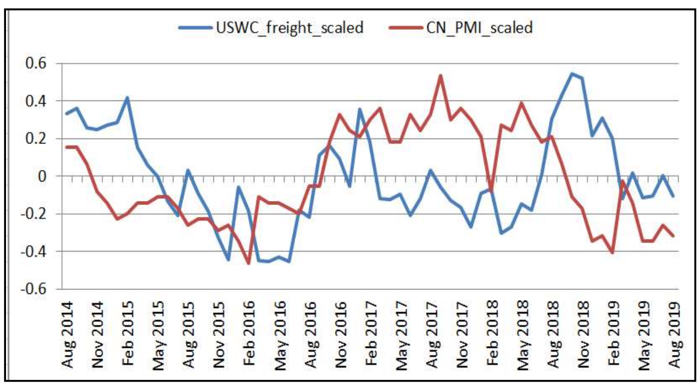


## China –US West Coast (USWC)

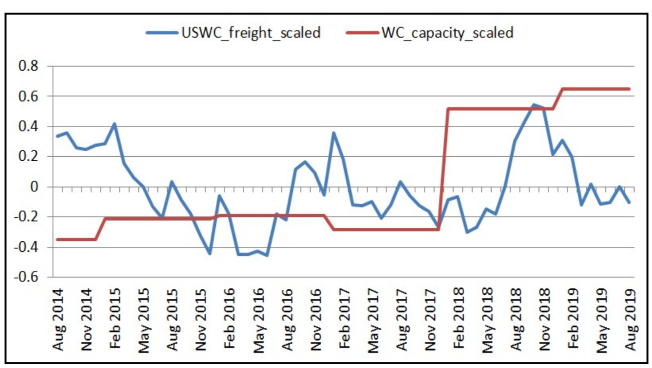
- US PMI vs. China –USEC spot ocean freight rate




- China PMI vs. China –USWC spot ocean freight rate




- EC shipping capacity vs. China –USEC spot ocean freight rate



# Appendix H: Correlation Analysis for the WC and EC Shipping Capacities

Very strongly correlation (>0.7); Strong correlation (0.5~0.7)

Medium correlation (0.3~0.5); Weak correlation (<0.3)

- China

| | | Date | USWC_freight_scaled | USEC_freight_scaled | Oil_Price_scaled | CNY_USD_scaled | China_CPI_NSA_scaled | US_CPI_NSA_scaled | CN_GDP_scaled | US_GDP_scaled | WC_capacity_scaled | EC_capacity_scaled | CN_PMI_scaled | US_PMI_scaled |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| WC_capacity_scaled | Pearson Correlation | .835** | 0.129 | -0.085 | .372** | .382** | .557** | .863** | .680** | .876** | 1 | .433** | -0.202 | 0.185 |
| | Sig. (2-tailed) | 0.000 | 0.320 | 0.516 | 0.003 | 0.002 | 0.000 | 0.000 | 0.000 | 0.000 | | 0.000 | 0.119 | 0.153 |
| | N | 61 | 61 | 61 | 61 | 61 | 61 | 61 | 61 | 61 | 61 | 61 | 61 | 61 |
| EC_capacity_scaled | Pearson Correlation | .355** | 0.001 | .322* | -0.010 | 0.045 | 0.000 | .337** | 0.215 | .382** | .433** | 1 | -.325* | -0.189 |
| | Sig. (2-tailed) | 0.005 | 0.995 | 0.011 | 0.941 | 0.730 | 0.999 | 0.008 | 0.096 | 0.002 | 0.000 | | 0.011 | 0.145 |
| | N | 61 | 61 | 61 | 61 | 61 | 61 | 61 | 61 | 61 | 61 | 61 | 61 | 61 |

- Indonesia

| | | Date | IDJKT_USEC_scaled | IDJKT_USWC_scaled | Oil_Price_scaled | IDR_USD_scaled | ID_CPI_NSA_scaled | US_CPI_NSA_scaled | ID_GDP_scaled | US_GDP_scaled | WC_capacity_scaled | EC_capacity_scaled | ID_PMI_scaled | US_PMI_scaled |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| WC_capacity_scaled | Pearson Correlation | .870** | 0.127 | 0.096 | .365** | .705** | .844** | .898** | .873** | .908** | 1 | .456** | .529** | 0.249 |
| | Sig. (2-tailed) | 0.000 | 0.353 | 0.481 | 0.006 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | | 0.000 | 0.000 | 0.065 |
| | N | 56 | 56 | 56 | 56 | 56 | 56 | 56 | 56 | 56 | 56 | 56 | 56 | 56 |
| EC_capacity_scaled | Pearson Correlation | .387** | .363** | -0.015 | -0.017 | .536** | .393** | .369** | .375** | .411** | .456** | 1 | -0.214 | -0.175 |
| | Sig. (2-tailed) | 0.003 | 0.006 | 0.912 | 0.902 | 0.000 | 0.003 | 0.005 | 0.004 | 0.002 | 0.000 | | 0.112 | 0.196 |
| | N | 56 | 56 | 56 | 56 | 56 | 56 | 56 | 56 | 56 | 56 | 56 | 56 | 56 |

- The Philippines

| | | Date | PHMNL_USEC_scaled | PHMNL_USWC_scaled | Oil_Price_scaled | PHP_USD_scaled | PH_CPI_NSA_scaled | US_CPI_NSA_scaled | PH_GDP_scaled | US_GDP_scaled | WC_capacity_scaled | EC_capacity_scaled | PH_PMI_scaled | US_PMI_scaled |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| WC_capacity_scaled | Pearson Correlation | .782** | -0.033 | 0.247 | .750** | .754** | .874** | .824** | .644** | .835** | 1 | 0.064 | -0.085 | .633** |
| | Sig. (2-tailed) | 0.000 | 0.832 | 0.111 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | | 0.684 | 0.590 | 0.000 |
| | N | 43 | 43 | 43 | 43 | 43 | 43 | 43 | 43 | 43 | 43 | 43 | 43 | 43 |
| EC_capacity_scaled | Pearson Correlation | -0.249 | .603** | 0.288 | .368* | -0.205 | -0.039 | -0.115 | -0.174 | -0.118 | 0.064 | 1 | -0.277 | 0.074 |
| | Sig. (2-tailed) | 0.107 | 0.000 | 0.061 | 0.015 | 0.186 | 0.802 | 0.465 | 0.264 | 0.452 | 0.684 | | 0.072 | 0.639 |
| | N | 43 | 43 | 43 | 43 | 43 | 43 | 43 | 43 | 43 | 43 | 43 | 43 | 43 |

- Singapore

| | | Date | SGSIN_USEC_scaled | SGSIN_USWC_scaled | Oil_Price_scaled | SGD_USD_scaled | SG_CPI_NSA_scaled | US_CPI_NSA_scaled | US_GDP_scaled | WC_capacity_scaled | EC_capacity_scaled | SG_PMI_scaled | US_PMI_scaled |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| WC_capacity_scaled | Pearson Correlation | .868** | 0.047 | 0.041 | .351** | -0.081 | .495** | .895** | .905** | 1 | .435** | .402** | 0.227 |
| | Sig. (2-tailed) | 0.000 | 0.733 | 0.766 | 0.009 | 0.554 | 0.000 | 0.000 | 0.000 | | 0.001 | 0.002 | 0.096 |
| | N | 55 | 55 | 55 | 55 | 55 | 55 | 55 | 55 | 55 | 55 | 55 | 55 |
| EC_capacity_scaled | Pearson Correlation | .358** | .267* | -0.051 | -0.032 | 0.237 | .278* | .336* | .382** | .435** | 1 | -0.089 | -0.216 |
| | Sig. (2-tailed) | 0.007 | 0.048 | 0.709 | 0.815 | 0.081 | 0.040 | 0.012 | 0.004 | 0.001 | | 0.519 | 0.113 |
| | N | 55 | 55 | 55 | 55 | 55 | 55 | 55 | 55 | 55 | 55 | 55 | 55 |

- Thailand

| | | Date | THLCH_USEC_scaled | THLCH_USWC_scaled | Oil_Price_scaled | THB_USD_scaled | TH_CPI_NSA_scaled | US_CPI_NSA_scaled | TH_GDP_Scaled | US_GDP_scaled | WC_capacity_scaled | EC_capacity_scaled | US_PMI_scaled |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| WC_capacity_scaled | Pearson Correlation | .849** | 0.147 | 0.110 | .350* | -.620** | .797** | .881** | .757** | .892** | 1 | .385** | .368** |
| | Sig. (2-tailed) | 0.000 | 0.299 | 0.437 | 0.011 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | | 0.005 | 0.007 |
| | N | 52 | 52 | 52 | 52 | 52 | 52 | 52 | 52 | 52 | 52 | 52 | 52 |
| EC_capacity_scaled | Pearson Correlation | .310* | .457** | 0.007 | -0.039 | -0.260 | 0.175 | 0.272 | 0.181 | .326* | .385** | 1 | -0.141 |
| | Sig. (2-tailed) | 0.025 | 0.001 | 0.962 | 0.785 | 0.063 | 0.214 | 0.051 | 0.198 | 0.018 | 0.005 | | 0.319 |
| | N | 52 | 52 | 52 | 52 | 52 | 52 | 52 | 52 | 52 | 52 | 52 | 52 |

- Malaysia

| | | Date | MYPKG_USEC_scaled | MYPKG_USWC_scaled | MYTPP_USEC_scaled | MYTPP_USWC_scaled | Oil_Price_Scaled | MYR_USD_scaled | MY_CPI_NSA_scaled | US_CPI_NSA_scaled | MY_GDP_scaled | US_GDP_scaled | WC_capacity_scaled | EC_capacity_scaled | US_PMI_scaled |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| WC_capacity_scaled | Pearson Correlation | .794** | 0.249 | 0.069 | -0.148 | 0.051 | 0.146 | 0.208 | .699** | .845** | .749** | .852** | 1 | 0.244 | .467** |
| | Sig. (2-tailed) | 0.000 | 0.075 | 0.629 | 0.296 | 0.722 | 0.303 | 0.139 | 0.000 | 0.000 | 0.000 | 0.000 | | 0.081 | 0.000 |
| | N | 52 | 52 | 52 | 52 | 52 | 52 | 52 | 52 | 52 | 52 | 52 | 52 | 52 | 52 |
| EC_capacity_scaled | Pearson Correlation | 0.194 | .534** | -0.081 | .415** | -0.066 | -.277* | .288* | 0.177 | 0.105 | 0.136 | 0.209 | 0.244 | 1 | -0.134 |
| | Sig. (2-tailed) | 0.169 | 0.000 | 0.568 | 0.002 | 0.641 | 0.047 | 0.038 | 0.208 | 0.457 | 0.336 | 0.137 | 0.081 | | 0.344 |
| | N | 52 | 52 | 52 | 52 | 52 | 52 | 52 | 52 | 52 | 52 | 52 | 52 | 52 | 52 |

- Vietnam

| | | Date | VNSGN_USEC_scaled | VNSGN_USWC_scaled | Oil_Price_scaled | VND_USD_scaled | VN_CPI_NSA_scaled | US_CPI_NSA_scaled | US_GDP_scaled | WC_capacity_scaled | EC_capacity_scaled | US_PMI_scaled |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| WC_capacity_scaled | Pearson Correlation | .870** | -.285* | 0.082 | .361** | .748** | .892** | .898** | .908** | 1 | .436** | 0.256 |
| | Sig. (2-tailed) | 0.000 | 0.032 | 0.542 | 0.006 | 0.000 | 0.000 | 0.000 | 0.000 | | 0.001 | 0.055 |
| | N | 57 | 57 | 57 | 57 | 57 | 57 | 57 | 57 | 57 | 57 | 57 |
| EC_capacity_scaled | Pearson Correlation | .359** | .298* | -0.002 | -0.013 | .328* | .334* | .340** | .384** | .436** | 1 | -0.189 |
| | Sig. (2-tailed) | 0.006 | 0.024 | 0.988 | 0.922 | 0.013 | 0.011 | 0.010 | 0.003 | 0.001 | | 0.160 |
| | N | 57 | 57 | 57 | 57 | 57 | 57 | 57 | 57 | 57 | 57 | 57 |