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The Durability of Economic Indicators in Container Shipping Demand: A Case Study of East Asia–US Container Transport

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Abstract

In the maritime industry, it is vital to have reliable forecast of container shipping demand. Although indicators of economic conditions have been used in modelling container shipping demand on major routes such as those from East Asia to the US, the durations of such indicators' effects on container movement demand have not been systematically examined. To bridge this gap in research, this study identifies the important US economic indicators that significantly affect the volume of container movements, and empirically reveal the duration of such impacts. We apply the vector autoregression (VAR) model to study time-series data of container movement and economic indicators in the period between 2001 and 2019. The estimation results suggest that in the mainland China route, "building permission" receives high impact and has a duration of 14 months, reflecting the fact that China exports a high volume of housing-related goods to the US. Regarding the South Korea and Japan routes, where high volumes of machinery goods are exported to the US, the "index of industrial production" receives a high impact with 11 and 13 months' duration, respectively. On the Taiwan route, since several types of goods are transported with significant shares, "building permits" and "index of industrial production" have important effects albeit not as large as those observed on the routes of mainland China, South Korea and Japan.

Keywords: container demand forecast; time-series data; durability; vector error correction model

1. Introduction

The global maritime container trade has increased continuously over the last two decades (UNCTAD, 2019). Container movement forecasting is vital for maritime-related business activities such as vessel deployment and freight rate negotiations. Furthermore, forecasts of container movement are used to predict the stock price of shipping lines. Previous studies have developed forecasting models for the demand for container movement, and the throughput of important routes and ports (e.g., Schulze and Printz, 2010; Parola et al., 2020). The demand for container movement is derived from trade between countries (i.e. derived demand). Thus, in general, the economic conditions of importing countries significantly affect the demand for container movement (Stopford, 2008). The forecast of container movement thus often utilizes various socio-economic indicators of the importing countries. The gross domestic product (GDP) of the importing countries has been one of the most frequently used indicators, which is highly correlated with container demand (e.g. Tally, 2012; Shibasaki and Kawasaki, 2021). For example, the coefficient of correlation between real GDP in the United States (US) and the container movement from Asia to the US was 0.81 in the period between the 1st quarter of 2000 and the 2nd quarter of 2019. However, since GDP statistics released by many official agencies are only available at the quarterly base level, it is not always possible to use this indicator to forecast container movement on a monthly basis. In addition, the use of GDP to forecast container movement is limited to aggregate value estimation, which cannot be used for a specific type of goods (e.g., housing goods, machinery goods, etc.). This is because GDP indicates the overall economic conditions of the countries or regions. Container movements are likely to increase (decrease) when the economic situation of the importing country improves (deteriorates). Furthermore, economic impacts are likely to endure for several months as the effects pass on along the supply chain. For example, if the housing market is booming, the associated derived demands, such as that for furniture, can be expected to grow, and container movements consequently should increase for several months. If we can identify the corresponding durability of each economic indicator’s effect on container movement, more accurate and detailed forecast may be developed for container movement.

Several studies have conducted demand forecasting for cargo movements and port throughputs. Rashed et al. (2017) applied a time-series approach including the autoregressive integrated moving average (ARIMA) model to forecast port throughput at Antwerp. Fung (2010) developed forecast for container throughput by considering the interactive relationships between major ports in Asia using a vector error correction model (VECM). In the bulk shipping market, several studies on demand forecasting can be found. For example, Tsioumas et al. (2017) developed forecasts of the Baltic Dry Index (BDI) by developing a multivariate Vector Autoregressive model with exogenous variables (VARX). Duru et al. (2012) investigated the forecasting accuracy of the dry bulk shipping index using a fuzzy Delphi adjustment process. Based on the existing literatures, it can be understood that economic indicators considered in this study have been identified as significant on container demand by using time-series data. However, to our best knowledge, no studies to date have measured the durability of economic indicators on container movement. To explore this research opportunity, this study aims to identify the durability of economic indicators of importing countries on container movement on a monthly basis, so that demand forecasts can be developed for container movements on trunk lines. The notable originality of this paper is the clarification of their durability on container demand, which is seriously overlooked in existing literatures. Shipping activities related to trunk routes are important to the maritime industry, as it shapes international trade, shipping networks, port cooperation, competition and differentiation (Slack 1985; Lam and Yap 2011; Wang et al. 2012; Zhuang et al. 2014; Homsombat et al. 2015; Notteboom et al. 2017; Zhu et al. 2019). Therefore, we will focus on the analysis of trunk routes, with a case study conducted for Asia-US container shipping which is one of the most important trunk routes in the world. As for Asian exporting countries , we consider China, South Korea, Taiwan, and Japan, the top four countries in terms of container volume to the US in 2019. Furthermore, these countries and regions export different goods. For example, the majority of container cargo from China comprises housing-related goods, whereas that of Japan and South Korea comprises a lot of machinery related to automobiles. In this way, the container volume of top goods differs across countries, and thus US economic indicators are expected to affect container movement of each exporting country differently. Such variability in sample may improve estimation efficiency. In addition, it allows our study to identify the difference in significant economic indicators that affect container movement for each Asian country.

The remainder of this paper is structured as follows. Section 2 reviews the literature on forecasting maritime cargo demand. In Section 3, an overview of container movement from Asia to the US is described for a better understanding of the current status of our case study route. In Section 4, the model is developed using monthly-level time-series data for the Asia-US container movement as a case study. Because the model applies time-series data, the stationarity of the data is confirmed in this section. Subsequently, the validity of the model is checked by comparing the actual and estimated container movements for each month. In Section 5, the durability of economic indicators is discussed for each exporting country. Finally, conclusions and directions for further research are presented in Section 6.

2. Literature review

Demand forecasting for cargo movements and port throughputs is an important research topic due to market demand in this field, with such studies conducted on various geographical scales. Among these, forecasting container throughputs at ports are the major research targets. Fung (2010) developed forecasts of container throughput by incorporating various interactive relationships between major ports in East and Southeast Asia with VECM, which is one of the time-series analysis methods well developed in econometrics. They identified the earlier construction of new terminal was important for a higher growth of container throughput. Rashed et al. (2018) demonstrated the effect of economic development on container throughput. In particular, they identified a relationship between EU19 trade indices and container throughput in the Hamburg–Le Havre range of ports. Rashed et al. (2017) applied different univariate time-series approaches: the autoregressive integrated moving average (ARIMA) model, namely the ARIMA-intervention model, and the ARIMAX model with a leading economic index. They also recognized as industrial confidence indicator has generated significant positive impact on container throughput in Antwerp port. Kawasaki et al. (2020) used simulation-based analysis to forecast container throughput at Kobe and Osaka ports as a result of the consolidation and privatization of the two ports. Chan et al. (2018) compared several time-series forecasting methods, including machine learning-based methods such as support vector regression (SVR) to forecast the port's container throughput using historical data. Some studies have adopted machine learning to forecast future container demand. In Moscoso-López et al. (2016), two forecasting models are presented and compared to predict the freight volume in the Algeciras port. The models developed and tested are based on artificial neural networks (ANN) and support vector machines (SVM). Both techniques are based on historical data of cargo volume itself, and these methods forecast the daily weight of the freight one week in advance. Bao et al. (2016) proposed a new BDI forecasting model based on a support vector machine combined with correlation-based feature selection (CFS). Tsai and Huang (2014) used ANN to predict container flows by considering GDP, industrial production index, interest rates, the value of the export and import trade, the number of export and import containers, and the number of quay cranes. Gosasang et al. (2011) compared linear regression model and neural network for forecasting container demand in Thailand. They identified crucial factors including GDP, interest rate, exchange rate, and population. Darendeli et al. (2020) applied machine learning for forecasting container demand by using gross domestic product (GDP), inflation rate, and exchange rate. Several studies (e.g., Vuchelen, 2004) addressed the strong positive association between consumer sentiment and economic condition. Since economic condition is one of the most significant factors affecting trade volume, consumer sentiment index is likely to be a vital factor for forecasting container volume. In addition, container demand itself could not be changed by the governments subsidies scheme to own the ports (Kawasaki et al., 2019).

Freight demand forecasting for bulk cargo is also a popular research field because of the public availability of several time-series data. For example, Tsioumas et al. (2017) examined the accuracy of the BDI by VARX, which also uses historical time-series data. Duru et al. (2012) proposed a fuzzy-DELPHI adjustment process to improve accuracy and performance in the validation of adjustments of statistical forecasts in the dry bulk shipping index. Kawasaki and Matsuda (2015) developed a logit-based model to forecast container and bulk shipping for wood pulp transport between East Asia and the US. Li et al. (2018), Papapostolou et al. (2016) and Papapostolou et al. (2014) addressed that consideration of sentiment index for future demand forecasting in shipping industry. However, to the best of our knowledge no study to date has measured the impact and durability of economic indicators on container movement.

To bridge the gap in the literature in terms of the impact of economic indicators and their durability, we developed a time-series model of the container movement from East Asia to the US. The notable advantage of clarifying the durability of an economic indicator is its practical application. If we can identify for how long an economic indicator persists, its impact, ship deployment, and container allocation plans can be efficiently conducted. In addition, detailed container demand forecasting can be used for many other applications, such as forecasting the stock prices of shipping lines, and predict the economic development trend. Demand forecasting of container movements on trunk lines are particularly important, as they play important roles in the understanding of the maritime sector, international trade and global economic development.

3. Overview of container movement from East Asia to the US

Container movement from East Asia to the US is one of the most important shipping routes in the world since its volume is substantially higher than that of the other routes (i.e., in 2019, the East Asia to US route occupied an 11.5% share of the world market) according to the IHS Markit database. In particular, container movement from East Asia to the US is of high volume since many goods are manufactured in Asia and consumed in the US. Shipment from the US to East Asia, in another direction, is approximately half of that outbound to the US, and generally transports lower-valued goods such as salvaged wastepaper (Tran et al., 2021). For the above reasons, our analysis targets sea routes linking four East Asian economies to the US, namely mainland China, South Korea, Taiwan, and Japan.

In this study, the Port of Import/Export Reporting Service (PIERS) database was used for monthly container movement data from East Asia to the US in the period between 2001 and 2019. Figure 1 shows the yearly container movements for each loading East Asian country to the US from 2001 to 2019. From this figure, it can be understood that mainland China export occupies the majority of the container volume of these four East Asian economies (i.e., 82.1% in 2019) to the US. As for the other three economies, Japan used to have higher volume than South Korea and Taiwan. However, South Korea- and Taiwan-originated container cargoes took over that of Japanese cargo in 2013 and 2019, respectively. One of the reasons for this shift is the change in Japan's industrial structure. In the 2000s and 2010s, the main exporting goods changed from final products to intermediate products (METI, 2020). Since intermediate products are physically smaller than final products and are mainly transported to Asian countries where final products are produced and shipped to consuming countries such as the US and EU, container volumes from Japan to final export destination countries have been decreasing.

Table 1 presents the container volume for each type of goods of each loading country in 2019. From mainland China, "furniture and household goods" has an overwhelmingly high share at 15.0% (1,586,000 TEU). This share accounts for 94.9% of total furniture and household goods transported from East Asia to the US. As for South Korea and Japan, "automobile parts" and "machinery" are the major goods for export to the US. South Korea and Japan are in competition with each other with respect to their top export goods. In the Taiwan route, "furniture and household goods" and "machinery"' are the top goods transported, and these are also the top goods exported from mainland China, South Korea, and Japan. These fundamental statistics demonstrate that each economy handles different goods; thus, it is expected that the container movement of each sea route is affected by different economic indicators.

[Insert Figure 1 near here.]

[Insert Table 1 near here.]

4. Model

4.1 Explanatory variables of the VAR model

In this study, the durability of economic indicators on container movements is identified by a vector autoregression (VAR) model using monthly-based time-series data. In the VAR model, we can analyze the effect of economic indicators at *t-k* on container movement at time *t* (Hamilton, 1994). In our model, we consider nine US economic indicators as explanatory variables that are likely to affect container movements. Time-series data are used for 228 months from January 2001 to December 2019. During this period, there were several major events affecting container movement volume from Asia to the US, such as the bursts of the dot-com bubble in the 2000s, the housing bubble in the late 2000s and early 2010s, and the subprime mortgage crisis between 2007 and 2010 in the US. Since US economic indicators reflect these economic events, our model implicitly incorporates the shocks associated with these events. The following are the explanatory variables considered in this study.

(1) Container movement volume (Y)

The container movement volume, which is the dependent variable of this study, was obtained from the Port Import Export Reporting Service (PIERS) database. Since the PIERS database reports purely observed value, seasonal fluctuations including holidays are not excluded. For example, China's export volume decreases during the month of the Chinese New Year, which is January or February. This kind of seasonal fluctuations are smoothed out from the time series data using the moving average method, so that the effect of economic indicators on container movement volume can be properly observed. Note that the dependent variable (i.e., container movement volume) of *t-k* months ago can also be one of the explanatory variables in VAR analysis. However, our objective is to identify the effect of economic indicators and their durability, and thus, the container movement data are only used for the dependent variable.

(2) Exchange rate (ER)

Exchange rate is likely to be one of the most significant variables affecting the volume of international trade. For example, when the Chinese Yuan strengthened against the US Dollar, Chinese cargo lost a lot of its price competitiveness. Consequently, the container volume from China decreased. For this reason, we consider the exchange rate of each currency against the US Dollar. The data were obtained from the Federal Reserve Board (FRB), and the average value of a month is used.

(3) Leading Economic Index (LEI)

In the US, the Leading Economic Index (LEI) is one of the most well-known indicators of the US's comprehensive economic condition. This indicator is released monthly by The Conference Board, Inc., which is a non-profit business membership and research group organization. This indicator is calculated on the basis of 10 sub-indicators, including average weekly working hours in manufacturing, average weekly initial claims for unemployment insurance, manufacturers' new orders for consumer goods and materials, ISM Index of New Orders, manufacturers' new orders for nondefense capital goods excluding aircraft orders, building permits for new private housing units, stock prices of 500 common stocks, Leading Credit Index (LCI), interest rate spread of 10-year Treasury bonds less federal funds, and average consumer expectations for business conditions. These data were calculated based on a questionnaire survey with 5,000 respondents extracted randomly. If the US economic condition is expected to be good, consumption demand will increase. Thus, the container importing volume also increases.

(4) Consumer sentiment index

In the US, consumption activity significantly affects the US economy since consumption occupied approximately 70% of the total real GDP in 2019, according to the US Bureau of Economic Analysis. The University of Michigan Consumer Sentiment Index is released monthly by the University of Michigan Surveys of Consumers, which expresses the consumer's expectations of US economic conditions in the near future. These data are derived on the basis of a questionnaire survey with 500 respondents, excluding the states of Alaska and Hawaii.

(5) Non-farm payroll (EN)

In the US, non-farm sectors account for approximately 95% of real GDP (Clayton, 2018). Thus, labor-related statistics in non-farm sectors should be important information for refracting the economic condition of the US. In this study, we incorporate non-farm payrolls, which are released monthly by the US Department of Labor Bureau of Labor Statistics. This statistic is developed based on the payrolls of approximately 350,000 non-farm private enterprises. It can be considered that if this statistic is in a good condition, the US economy will be upturned; thus, container demand will increase.

(6) Unemployment rate (UR)

The unemployment rate is one of the significant labor force-related statistics that is sometimes used as a leading indicator of economic recession (Clayton, 2018). Thus, this statistic seems to be useful for early identification of a reduction in container demand. The data can be obtained monthly from the US Census Bureau of the Department of Commerce.

(7) Manufacturing the ISM Report on Business (PMI)

As addressed in Section 2, manufacturing-related goods such as automobile parts and machinery are one of the major type of goods exported from Asia to the US, particularly from South Korea, Taiwan, and Japan. Thus, these data seem to be a significant leading indicator of container demand from these economies. The Manufacturing ISM Report On Business is published monthly by the Institute for Supply Management (ISM). It is based on a national survey of purchasing managers' tracking changes in the manufacturing and non-manufacturing sectors and is considered to be one of the most reliable economic barometers of the US economy that provides an important early look at its economic health (Baumohl, 2012).

(8) Building permits (BP)

In Asia-to-US container movement, approximately 20% of the cargo comprises housing-related goods such as furniture and building materials. Thus, new building is an important indicator of container demand. In addition, new buildings foster several derived demands, including furniture, curtains, carpets, etc. For this reason, the impact of this indicator on container demand seems to have long durability. This study uses building permits data, which are released monthly by the US Census Bureau of the Department of Commerce. These data are widely known as a leading indicator of US economic conditions. When economic conditions are good, this indicator increases.

(9) Indices of Industrial Production (IIP)

As is widely known, GDP has a strong correlation with container demand (Stopford, 2008). However, GDP cannot be used in this study because it is available as quarterly-based data. Thus, we use the indices of industrial production (IIP) as a proxy of GDP since these indicators are strongly correlated with each other (Clayton, 2018). IIP is released monthly by the FRB and is composed of 295 individual statistics related to production in a wide variety of sectors.

(10) Dow Jones Industrial Average (DJI)

The Dow Jones Industrial Average is an indicator of the US stock market published by Dow Jones & Company, Inc. This indicator is a stock market index that measures the stock performance of 30 large companies listed on stock exchanges in the US. The value of the index comprises the sum of the stock prices of the companies included in the index, divided by a factor that, as of September 2020, is approximately 0.152. The factor changes whenever a constituent company undergoes a stock split so that the value of the index is unaffected by the stock split. Stock price is known as a leading indicator of economic boom and recession; thus, it is expected to be related to container demand.

Using the above 10 economic indicators that are likely to be related to container movement from Asia to the US, the durability and impact on container movement are identified.

4.2 Data processing

4.2.1 Unit root test

In this study, the VAR model is used to analyze the durability and impact of economic indicators on container movement from Asian economies to the US. In the VAR model, it is possible to identify the effect of economic indicators (i.e., explanatory variable) at t-k time on container movement (i.e., dependent variable) at *time t*. Meanwhile, durability can be identified using the concept of impulse responsive function (Hamilton, 1994). The input data comprise monthly time-series data between 2001 and 2019. To avoid spurious correlations between the variables, the stationarity of all input variables needs to be satisfied. Suppose we have time series data y_i, and defined container movement volume y_t at time t and y_{t-k} at k time before. When mean $[E(y_t)]$, variance $[Var(y_t)]$, and autocorrelation $[Cov(y_t, y_{t-k})]$ are constant, as shown in Equations (1)–(3) against the passage of time, the time series process y_i is identified to satisfy the stationarity. Note that autocorrelation is defined as the correlation between time t and t-k of the same variable.

$$E(y_t) = \mu \tag{1}$$

$$Var(y_t) = E\left[(y_t - \mu)^2\right] = \gamma_0 \tag{2}$$

$$Cov(y_t, y_{t-k}) = E\left[(y_t - \mu)(y_{t-k} - \mu)\right] = \gamma_k \tag{3}$$

μ, γ_0, and γ_k indicate the mean, variance, and autocorrelation of the time series data of y_i, respectively. To statistically test the existence of stationarity of the time series process, a unit root test is applied. In this study, the Augmented Dickey-Fuller (ADF) test is applied for the unit root test. Equation (4) is used for the ADF test.

$$\Delta y_t = (\alpha - 1) y_{t-1} + \sum_i \beta_i \Delta y_{t-i} + \mu + e_t \tag{4}$$

Here, i is called the lag number. For example, in the case of i=n, the data of n time period before are used for the ADF test, while e_t denotes the error term at time t. In Equation (4), the null hypothesis is set as α-1=0 to test the existence of a unit root. In other words, there is a unit root in the case of α=1. In general, the original time series does not have a unit root in many cases. In our study, there is no unit root in the original time series; thus, we show the results of the unit root test for the first difference of a time series in Table 2. Note that the first difference of a time series is the series of changes from one period to the next.

[Insert Table 2 near here.]

In the ADF test, one needs to determine the number of lags. Considering the monthly input data, the number of lags is set to 12 as the maximum number. Subsequently, i is obtained at the minimum Akaike's information criteria (AIC). Note that the original time-series data do not have unit roots for the *EN*, *PMI*, *IIP*, *MI*, *DJ*, and *ER* of South Korea and Taiwan. In the case of the first difference of a time-series data, all data confirm the existence of stationarity at the 5% significance level, as shown in Table 2. Consequently, we adopt the first difference of a time-series data for the VAR model development.

4.2.2 Cointegration test

In the specification of the VAR model using the first difference of a time-series data, cointegration between the variables is likely to exist. In case there is a cointegration between the variables, the vector error correction model (VECM) is used to identify the causal relationship between each explanatory variable and the dependent variable. Thus, a cointegration test was conducted using the maximum eigenvalue and trace test so that the existence of cointegration and its number were identified. As a result of the cointegration test, cointegration for mainland China export was identified as 2 and 3 by the maximum eigenvalue and trace test, respectively, at the 5% significance level. Similarly, the cointegration of South Korea, Taiwan, and Japan export cases are also identified as 3, 3, and 4, respectively, using trace tests. Since cointegrations are identified in all sea routes, the VECM is used for model specification. In the VECM, one needs to determine the number of cointegrations, which normally adopt a larger value among the cointegrations identified by the maximum eigenvalue and trace value. Consequently, the number of cointegrations is three for China, three for South Korea, three for Taiwan, and four for Japan.

4.3 Specification of the model

Before estimating the model parameters, a correlation analysis is conducted between the explanatory variables to avoid multicollinearity and build a robust model. The results of the correlation analysis suggest that the number of nonfarm employment has a high correlation of 0.42 with the industrial production index. Since the model has an employment-related variable such as unemployment rate, the number of nonfarm employees is excluded from the explanatory variables. The correlation between LEI and the number of building permits is relatively high at 0.41. Housing-related goods are of particularly high volume in China and Taiwan exports, and the LEI is somewhat highly correlated with the Industrial Production Index and building permits at 0.50 and 0.41, respectively. We therefore exclude the LEI and retain the IIP and the number of building permits in the model. No other correlations greater than 0.20 are found between the above variables. Six variables are thus used as explanatory variables: exchange rate, consumer confidence index, building permits, industrial production index, unemployment rate, and Dow Jones average. In this study, the VECM is expressed as equations (5) and (6) because the data comprise a first difference series.

$$Y_t = \alpha \cdot EC_{t-1} + \sum_{i=1}^{p-1} \gamma_i \cdot \Delta Y_{t-i} + u_t \tag{5}$$

$$EC_{t-1} = \beta_1 Y_{t-1} + \beta_2 ER_{t-1}^{country_i} + \beta_3 CS_{t-1} + \beta_4 UR_{t-1} + \beta_5 PMI_{t-1} + \beta_6 BP_{t-1} + \beta_7 IIP_{t-1} + \beta_8 DJI_{t-1} \quad (6)$$

α, EC, γ, β, and u are column vectors of the coefficient, correction terms, coefficients of variables, column vectors of errors, and constant terms, respectively. Parameter estimation requires the number of lags (p) to be determined. The results of the AIC test show that the optimal number of lags, where the AIC is minimized for all routes, is 2. Therefore, we specify the model as 2 for the number of lags.

The results of the parameter estimation are shown in Table 3. Although it is possible to observe the interrelationships between all the variables used in the model in the VECM, since the purpose of this study is to examine the impact of each economic indicator on the container cargo volume, only those results pertaining to the case where the container cargo volume is the dependent variable are reported. The overall trend is that the coefficients of the China export model are relatively large. For example, for the Consumer Sentiment Index (*CS*), the coefficients are four digits (-1,479.87, -2,123.93) for the Chinese shipment, while they are two or three digits for other routes. This result suggests that the impact of the economic indicators on the container demand per unit change in the economic indicator is relatively large for Chinese shipments. Since the volume of cargo movement from China is overwhelmingly higher than that on other routes, this result is considered reasonable.

[Insert Table 3 near here.]

4.4 Validity of the model

To check the validity of the constructed model (Table 3), the scatter plots shown in Figure 2(a)–(d) are prepared for each country's exports. The horizontal axis represents the actual value for each month, while the vertical axis represents the estimated value for each month. In the scatter plots, a regression linear line with a slope of 1 through the origin is drawn. If the model perfectly reproduced the actual values, the coefficient of determination of the regression line would be one. As the coefficient of determination approaches zero, it is interpreted as less reproducible. The coefficients of determination for the Chinese, Korean, and Japanese exports are 0.87, 0.83, and 0.75, respectively, which suggest high reproducibility. On the other hand, the coefficient of determination for Taiwanese exports is 0.60, which is high in terms of absolute value, but the reproducibility is relatively low compared to other routes. The top commodities transported on the Taiwan-shipped routes are composed of various items such as automobile, machinery, and housing-related products. The

Taiwanese shipment of a relatively wide variety of commodities is influenced by various factors and is more difficult to predict than other routes. To solve this problem, new explanatory variables can be added even with the current high coefficient of determination of 0.68. However, because the same explanatory variables are used on all routes, for consistency and benchmarking purpose, the model identified in Table 4 will be used to proceed with the discussion.

[Insert Figure 2 near here.]

5. Effect and durability of economic indicators

Using the identified model shown in Table 4, the impulse reaction function is used to identify the extent to which container cargo movements change and persist when each economic indicator is changed by one standard deviation at t=0. Figure 3 (a)–(d) show the results of the impulse reaction functions for shipments from each economy. The horizontal axis represents the monthly change over time, while the vertical axis is the cumulative change in container cargo movements (unit: TEU) in response to changes in each economic indicator t=k months after the change of one standard deviation of each economic indicator at t=0. For example, the increase or decrease in container cargo movements after one month (t=1) of a one standard deviation increase in the economic indicator at t=0 is shown in the "1" on the horizontal axis, while the cumulative container cargo movements after 24 months are shown in the "24" on the horizontal axis. The convergence condition of the durability of container cargo movements was set to be when the relative error of the month-to-month cargo movements is less than a sufficiently small value (ε_G), as shown in Equation (7). Although there is no clear standard for setting ε_G (Barrett, 1994), it is set to 0.01 in this study.

$$\sqrt{(y_t - y_{t-1})^2} \Big/ |y_t| < \varepsilon_G \tag{7}$$

Under these conditions, the period during which each economic indicator significantly affects the volume of container cargo movement is shown as a solid line in Figure 3. Subsequently, the solid line is crossed out for economic indicators at t-k that have ceased to persist (i.e., converged).

First, the results are discussed in terms of the Chinese route shown in Figure 3(a). With regard to the exchange rate, it is clear that the weakening of the US Dollar against the Chinese Yuan had a negative impact that persisted for 10 months. In total, the volume of cargo movements decreased by 1,774 TEUs and weakened the standard deviation of the US Dollar. The most positive impact on China's export volume is caused by the number of building permits, which lasted for 14 months with an increase of 9,654 TEU. The results are in line with expectations, as furniture and household goods (i.e., furniture and household goods and plastic products for flooring, blinds) accounted for 21.2% of the total container volumes in Chinese export and are heavily influenced by trends in the US housing market. However, its effect is smaller than the other indicators after the changes (i.e., 1–4 months after the change) due to the time lag between building permit and container demand. On the other hand, PMI, DJI, and IIP have a higher positive impact on the container volume than that of BP in the early stages (i.e., 1–4 months after the change). In particular, PMI has a relatively high impact with a 6,594 TEU increase in volume after four months. The timing and magnitude of the impact of economic indicators vary. Therefore, it can be suggested that when forecasting container cargo movements, not only the extent to which each economic indicator affects the volume of cargo movement, but also the different timing of its manifestation should be considered.

For the South Korean shipment shown in Figure 3(b) and the Japanese shipment shown in Figure 3(d), the impact of IIP is significant because the top cargoes include a large share of machinery, such as automobile-related products and general electronics equipment. It can be observed that the influence of the IIP tends to become evident at the early stage in both countries. Subsequently, its impacts are gradually increasing for South Korean cargo and decreasing for Japanese cargo. Therefore, it should be noted that a relatively large change in cargo movements is expected to occur immediately after the change in IIP in the forecast of container cargo movements in both countries. In addition, the impact of PMI is the largest for South Korean cargo with 10 months' duration. The duration of the consumer sentiment index persists for 16 months for the Korean shipment, while the building permit persists for 15 months for the Japanese shipment, which is the longest duration of impact. Similar to Chinese shipments, the exchange rate for South Korean and Japanese shipments had a negative impact on container movement when the US dollar weakened against the currency of these countries.

For the Taiwanese shipment shown in Figure 3(c), the index of industrial production is also found to have an early onset of impact. On the other hand, the number of building permits ultimately has the largest impact, although it appears relatively later. The top-ranking cargoes in Taiwan are less concentrated on specific commodities; thus, the impact of each economic indicator on the volume of cargo movement after convergence is smaller than that of other economies, ranging from -30 to 270 TEUs. The industrial production index and building permits have similar impacts. Therefore, when forecasting Taiwanese container cargo movements, one needs to pay attention to the movements immediately after the change in economic indicators of the IIP and building permits.

[Insert Figure 3 near here.]

6. Conclusion

In this study, we investigate the duration of US economic indicators for container movements from East Asian countries to the US. A model is developed for shipments from large East Asian countries and regions such as mainland China, South Korea, Taiwan, and Japan. This is the first attempt for identifying the durability of the impact of economic indicators on container movements, which is especially valuable information for maritime-related business such as vessel deployment, manufacture's business plan, and freight rate negotiation. As for shipping lines, our results can provide directions for portfolio analysis of vessel deployment and investment. Since our results provide a durability of the impact of change in economic indicators, proper vessel deployment and space chartering can be conducted although sudden adjustments in vessel deployment is not easy for shipping lines. Besides, manufacturers in exporting countries and consignees in importing countries make proper decision making for change in their production volume according to the change in economic indicators. The findings demonstrate that each economy is affected by different economic indicators with different durations. In the Chinese shipment, the number of building permits has a significant impact because there is a large share of housing-related products, and their impact on the shipment continues for 14 months, which is the longest duration for Chinese shipment. For the Korean and Japanese shipments, which transport a large volume of machinery-related goods, the industrial production index for both countries and PMI for South Korea had a significant impact. As for the effect on Taiwanese shipment, the impact of economic indicators was relatively smaller than that of other countries as an overall trend.

This study has several limitations. Because actual shipping volumes may be constrained by supply in the maritime sector, future works may include the development of a decision-making model for vessel allocation planning (timing, number of vessels, etc.). Also because there is no clear criterion for the convergence condition, in this study, the convergence condition was set based on an error criterion of less than 0.01 for the relative error of cargo movement in the previous month. However, the convergence values and persistence differ depending on the method of setting the error criterion; thus, further study is of good value . Furthermore, our study focuses on container transport between East Asia and US lead to a lack of generalization. The theoretical foundation for the identified patterns, such as the underlying linkage between building permit and export volume, is yet to be formulated. In doing so, we may further extend our study in different sectors (e.g., tanker, dry bulk) across different geographical regions (e.g., East Asia and Europe), and explore potential causal relationships among the indicators included in the study.

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