

Park, Sunghwa; Kwon, Janghan; Kim, Hanna; Ryu, Heeyoung; Kim, Taeil

**Article**

## Effect of macroeconomic shocks on the shipping market: Focusing on COVID-19 pandemic

Asian Journal of Shipping and Logistics (AJSL)

**Provided in Cooperation with:**

Korean Association of Shipping and Logistics, Seoul

*Suggested Citation:* Park, Sunghwa; Kwon, Janghan; Kim, Hanna; Ryu, Heeyoung; Kim, Taeil (2024) : Effect of macroeconomic shocks on the shipping market: Focusing on COVID-19 pandemic, Asian Journal of Shipping and Logistics (AJSL), ISSN 2352-4871, Elsevier, Amsterdam, Vol. 40, Iss. 2, pp. 89-102,  
<https://doi.org/10.1016/j.ajsl.2024.02.001>

This Version is available at:

<https://hdl.handle.net/10419/329737>

**Standard-Nutzungsbedingungen:**

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

**Terms of use:**

*Documents in EconStor may be saved and copied for your personal and scholarly purposes.*

*You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.*

*If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.*



<https://creativecommons.org/licenses/by-nc-nd/4.0/>

Mitglied der





## Effect of macroeconomic shocks on the shipping market: Focusing on COVID-19 pandemic



Sunghwa Park <sup>a</sup>, Janghan Kwon <sup>b,\*</sup>, Hanna Kim <sup>c</sup>, Heeyoung Ryu <sup>c</sup>, Taeil Kim <sup>c</sup>

<sup>a</sup> Department of International Trade, College of Business Administration, Gyeongsang National University, Jinju, South Korea

<sup>b</sup> Department of Global Business, Changwon National University, Changwon 51140, Korea

<sup>c</sup> Maritime Policy Research Department, Korea Maritime Institute, Busan, South Korea

### ARTICLE INFO

#### Keywords:

Macroeconomic shocks  
COVID-19 Pandemic  
Structural vector autoregressive  
Historical decomposition  
Forecast scenario analysis  
Traditional economic crisis  
Shipping market

### ABSTRACT

This study examines the effect of macroeconomic shocks on the shipping market using time-series data by comparing the periods of the COVID-19 and traditional crises. A structural vector autoregressive model and forecast scenario were applied for the analysis. The results can be summarized as follows. First, the response of freight rates to macroeconomic shocks in the shipping market was consistent with the theoretical predictions. Second, the freight rates were the most affected by VIX shock during the global financial crisis, by fleet development shock during the period of overbuilt shipping capacity, and by the oil price during the periods of instability in the oil market. In particular, we found that businesses recovered more quickly from the shock during the COVID-19 compared to other periods, implying that the uncertainty had a greater influence than real economic factors during the pandemic. Finally, forecast scenario analysis showed that freight rates fell sharply immediately after the global financial crisis and during COVID-19 but the pace of recovery was faster during the COVID-19 than the global financial crisis. This study is significant as it empirically shows that the main factors affecting the shipping market and its transition process differ according to the characteristics of episodes.

### 1. Introduction

The shipping industry is sensitive to global economic conditions. An economic event, such as a global financial crisis, immediately affects freight rates in the shipping market and can lead to a long-term recession in the industry. During the past few decades, the shipping industry has been going through a series of economic crises, including the 1970s oil shock and the following recession during the 1980s, the Asian financial crisis in 1997, and the global financial crisis in 2008, driving numerous shipping companies to bankruptcy or restructuring. Thus, an understanding of the global economy is crucial to understand shipping market conditions.

Recently, as the onset of the COVID-19 pandemic increased the fluctuations in the global financial market, with a global recession looming, some even raised the possibility that it would cause the worst global economic crisis in history. Furthermore, the pandemic-induced slump was expected to have a greater impact as the crisis, rather than following the business cycle theory, hit the different sectors—for example, finance, manufacturing, consumption, and logistics—simultaneously. According to the International Monetary Fund

(IMF), the global economic growth rate in 2020 was the worst since World War II, with  $-3.3\%$  worldwide,  $-3.5\%$  in the United States,  $-4.8\%$  in Japan,  $-4.9\%$  in Germany,  $-8.2\%$  in France,  $-8.9\%$  in Italy,  $-11.0\%$  in Spain,  $2.3\%$  in China, and  $-1.0\%$  in Korea (International Monetary Policy, 2021).

As the shipping industry is a derivative industry of the real economy, some were concerned that it would be hit hard by the economic slowdown due to COVID-19 and the resulting effects on the global manufacturing industry, centered around China. South Korean shipping companies estimated that their sales in March 2020 decreased by an average of 27.4% as compared to the same month of the previous year due to the impact of COVID-19, an impact similar to or greater than that of the global financial crisis (Korea Maritime Institute, 2020).

However, contrary to expectations, the stock market, a leading indicator of the real economy, is bouncing back in a “V-shaped” recovery; the Dow Jones Industrial Average has surpassed the 30,000 mark for the first time in 3 years and 10 months on November 24, 2020, and South Korea’s main Kospo index hit 3000 for the first time in 14 years on January 6, 2021. Concomitantly, economic transport shipping indexes, including the China Containerized Freight Index (CCFI) and Shanghai

\* Corresponding author.

E-mail address: [jkwon@changwon.ac.kr](mailto:jkwon@changwon.ac.kr) (J. Kwon).

Containerized Freight Index (SCFI), are surging. However, this rapid recovery is driven by active fiscal policies stimulating the economy in countries including the United States and increasing the supply of money to an all-time high; it remains to be seen whether the real economy will follow suit. The rise in CCFI can also be interpreted as the result of an inadequate supply of ships due to a recent and, possibly, temporary increase in demand after supply was reduced during the pandemic. The sudden emergence of the COVID-19 pandemic has prompted various governments to impose stringent lockdown measures to curb the spread of the virus. These measures have significantly affected the global trade market in terms of supply and demand. The aforementioned national lockdowns resulted in a significant decline in production levels, ultimately leading to an increase in unemployment rates. Subsequent to the relaxation of lockdown measures in various countries, global demand for trade in goods has increased. However, the pandemic-induced mass unemployment created issues in transport and logistics, resulting in logistical disruptions. The disruptions to U.S. West Coast ports forced unloading of cargo from a significant number of ships was delayed, causing a ripple effect worldwide and leading to a shortage of ships in Asia and Europe. Consequently, container freight rates sharply increased.

The COVID-19-induced economic crisis is distinctly different from the previous historical episodes in its fundamental causes and development, with uncertain prospects. Unlike the past crises, which originated from economic factors, this crisis was triggered by the paralysis of economic activities due to the pandemic and its disproportionate effects on industry.

Despite the signs of quick recovery in the shipping industry, there is a possibility that the global market will stagnate again if the spread of COVID-19 subsides and major advanced countries begin to recover liquidity. Furthermore, a substantial number of shipping companies that are not financially sound enough will likely face difficulties if the market slows down again.

Against this backdrop, it is crucial to understand the causes of and responses to past financial crises to effectively address the COVID-19 economic crisis. Simultaneously, we need to identify the factors influencing the shipping market during each historical episode with appropriate response strategies. This will enable the shipping industry to prepare appropriate plans to overcome the financial crisis.

The remainder of this study is organized as follows. **Section 2** analyzes previous research, focusing on differences from the current study; **Section 3** explains the method of analysis; **Section 4** describes the analysis data and discusses the results of empirical analysis and implications; and **Section 5** makes conclusions.

## 2. Literature review

The shipping market shows open and dynamic movement through continuous interaction with external economic conditions (Tsioumas et al., 2021:1). Therefore, global economic factors are instrumental to changing supply and demand in the shipping market (Bildirici, 2015). According to Stopford (2009), the demand for shipping increases as goods to be shipped are produced through various industrial activities in the world economy. Meanwhile, the supply of shipping—the capacity of ships, determined by the world fleet and new building order—is temporarily inelastic, as it takes time to build and deliver new ships. A growing body of research has been devoted to the analysis of interactions between external economic conditions and the shipping market to reflect the structural characteristics of the shipping industry and understand the shipping market better.

Among the (potential/actual) correlations between the shipping market and macroeconomic conditions, researchers have mostly focused on the fluctuations in freight rates and determinants. Klovland (2002) analyzed freight rates between 1850 and the World War I, suggesting that the fluctuation is closely related with the macroeconomic environment, especially the price of dry cargo (coal, metals). Freight rates

are considered a key indicator of the shipping market. Furthermore, Kilian (2009) created a monthly index of global real economy activity similar to the Baltic Dry Index (BDI) and set it as a variable for global demand to analyze the effect of the international oil price shock on the shipping business.

Several studies have suggested a significant correlation between macroeconomic variables and freight rates. Researchers have argued that industrial production, among other macroeconomic variables, is closely related to freight rate, and have identified international oil price as another main factor in freight rate changes (Beenstock & Vergottis, 1989, 1993; Kogan et al., 2009; Lyridis et al., 2014; Papapostolou et al., 2014; Gavriilidis et al., 2018; Lim et al., 2019; Michail, 2020). Recently, Michail (2020) reached the conclusion that the global economic growth is proportional to the demand for each ship type—such as containerships, bulk carriers, and tankers—and that oil prices are inversely related to the demand for each ship type.

Kavussanos and Marcoulis (2000) used the Multivariate Least Squares regression model to find that the price–earnings ratio of US maritime transportation companies is affected by macroeconomic variables, such as oil prices and industrial production. Grammenos & Arkoulis (2002) analyzed the factors affecting the stock price of shipping companies, with industrial production, inflation rate, oil price, exchange rate, and laid-up tonnage as explanatory variables. Syriopoulos and Roumpis (2009) and Papapostolou et al. (2014) revealed that macroeconomic shocks, such as the global financial crisis, are an important factor in determining the volatility of freight rates and affect the stock price and performance of shipping companies.

Some studies have analyzed the factors that influence freight rates through the price of raw materials. Tsioumas and Papadimitriou (2018) analyzed the lead–lag relationship between raw material prices and freight rates, using Granger's test and a Vector Autoregressive (VAR) model. With the prices of iron ore, coal, and wheat as the main variables, they concluded that the price of wheat preceded dry bulk freight rates. Angleopoulos et al. (2020) is another such study; they employed the dynamic factor model to analyze the lead–lag relationship between the price of 65 raw materials and major freight rates, confirming that the international oil price, among other raw materials, preceded the shipping rates.

In addition, a series of studies has analyzed the effect of financial variables on freight rates. Dikos et al. (2006) analyzed the tanker market using system dynamics and found that oil prices and London Interbank Offered Rate (LIBOR) interest rates are major factors in the fluctuations of the tanker market. Michail and Melas (2020) analyzed the impact of the COVID-19 pandemic on the shipping market through generalized autoregressive conditional heteroskedasticity (GARCH) model and the VAR model; the results revealed that the outbreak of the pandemic lowered freight rates, causing a negative impact on sea transportation demand. According to the authors, international oil prices and the stock market were the main channels through which the impact of the pandemic spread. Wu et al. (2021) found that the CBOE Volatility Index (VIX), signaling the level of fear in the market, is inversely related to dry cargo freight rates. Furthermore, the argument that VIX raises the predictability of the freight rates served as an indicator to measure the level of investment risk and stress in the market.

Studies have also been conducted to analyze the dynamic relationship between macroeconomic conditions and the shipping market, using impulse response function analysis through the structural model (Jiang et al., 2018; Yin et al., 2017). Ghiorghie and Gianina (2013) performed VAR analysis using annual data from 1985 to 2012 to examine the causal relationship between BDI and global economic growth rates; this analysis revealed that the relationship between BDI and economic growth rate was symmetrical and bidirectional. Chen et al. (2021) used the time-varying parameter vector autoregression with stochastic volatility (TVP-SV-VAR model) to explore the nonlinear dynamic adjustment relationship among the world oil market, the global shipping market, the stock market and the China's economic growth, and Gu et al. (2020)

analyzed the impact of the BDI shock on the Tianjin Shipping Index (TSI).

In addition, some studies that analyzed the relationship between macroeconomic variables and freight rates by classifying economic conditions or freight rates through structural models; these include Bildirici et al. (2015), Kutin et al. (2018), Park et al. (2021), Nomikos & Tsouknidis (2022), and Park et al. (2023). Bildirici et al. (2015) divided the economic phase (regime) into global financial crisis, general growth period, and growth period to analyze the relationship between US GDP growth rate and BDI using the Markov-switching vector autoresssive (MS-VAR) model. The results revealed that improvement in BDI had a positive effect on economic growth in the high growth period.

Kutin et al. (2018) also used MS-VAR model to analyze the relationship between CCFI, Clarksons average containership earnings, fleet development, price of crude oil, and global real economic activity (Kilian, 2009) by dividing shipping business regimes into Regime 1 (high volatility and decreasing freight rates) and Regime 2 (low volatility and high container freight rates). The results confirmed that each variable has a different effect on freight rates with regime changes.

Park et al. (2021) conducted an analysis of the effects of the global economy on maritime transport revenue and global shipbuilding contracts in Korea using the SVAR model, historical decomposition, and local projections. Meanwhile, Nomikos and Tsouknidis (2022) examined the impact of supply and demand on bulk freight rates using the SVAR model, historical decomposition, and forecast scenario analysis. Park et al. (2023) analysed the factors that impact BDI fluctuations in terms of demand, supply, and freight rate-specific demand, using the recursive SVAR model and historical decomposition. The authors disclosed that different factors influence freight rates in the shipping market during each major period. Specifically, speculative demand rather than normal supply and demand determines the freight rate during times of rapid fluctuations.

As an international business, the shipping market, especially shipping of dry cargo, is susceptible to geopolitical changes and global economic conditions. In other words, the long-term cycle of the global economy has a great impact on the shipping market (Scarsi, 2007). Therefore, negative macroeconomic changes, including the global financial crisis, also affect the spread of volatility in shipping costs (Tsouknidis, 2016). This means that it is important to understand the effect of global economic growth on shipping demand, which is determined by global industrial production (Población & Serna, 2018). As seaborne commodity trades increase, shipping freight rates rise and orders for new shipbuilding increase (Bai & Lam, 2019). It is essential to understand the sequential relationship between the macroeconomy, shipping demand, shipping supply, and freight rates to forecast shipping market trends.

In the analysis of macroeconomic conditions, oil price is a key variable. In particular, crude oil production, a supply-side variable, frequently appears as the most exogenous macroeconomic variable. Accordingly, research on methodologies for predicting oil prices by revealing factors causing fluctuation of oil prices—the most important variable in the crude oil market—and analyzing the impact of the shocks caused by crude oil demand and supply on oil prices has been prolific. The majority of the studies are based on the VAR model suggested by Sims (1980), with variations.

Freight rates in the shipping market are an important macroeconomic variable. As Kilian (2009) used the Global Real Economic Activity Index, created using dry freight rates, as a demand variable for oil prices, many studies have followed suit. Ghiorghie and Gianina (2013) argued that the BDI and economic growth have a significant influence on each other. Bildirici et al. (2015) stated that the BDI is the most important indicator in shipping costs to measure global trade and manufacturing activities. However, research on shipping freight rates has been conducted only sporadically and has focused on the lead-lag relationship between spot rates and futures, the relationship between freight rates and economic growth, and that between freight rates and ship prices.

Thus, there is a gap in the empirical analysis on the impact of supply and demand shocks on freight rates. In addition, previous investigations utilizing dynamic structural models have been restricted to exploring variable relationships throughout the analysis period. Consequently, the results produced may differ for identical variables and models in different analysis periods. This is particularly apparent during the global economic crisis where both global economic variables and shipping market variables undergo extreme fluctuations. Therefore, the factors that contribute to freight rates can deviate greatly. When forecasting freight rates using the analysed models from previous studies, predicting the effect of some severe shocks, such as the global economic crisis, is not feasible. This is due to the fact that the predicted value of the dependent variable is based on the relationship between variables observed during the analysis time frame.

The literature most closely related to this study is Nomikos and Tsouknidis (2022), who disentangled demand and supply shocks in the shipping freight market and found that demand shocks have a greater effect on real freight rates compared to supply shocks. They also performed the forecast scenario analysis to quantify the cumulative effect of all structural shocks. This study differs from Nomikos and Tsouknidis (2022) in the model specification, and the forecast scenarios. In terms of the model specification, Nomikos and Tsouknidis (2022) used a four-variate model consisting of trade, fleet, freight, and net contracting. By doing so, they attempted to investigate the impact of supply and demand shocks on net contracting. While this study utilized a five-variate model composed of VIX, oil price, merchandise trade, fleet development and freight to examine the effects of macroeconomic shocks on the shipping market. In terms of the forecast scenarios, this study adopted forecast scenarios related to historical episodes such as the Asian crisis (1997Q3–1999Q4), market boom (2006Q3–2008Q2), the global financial crisis (2008Q3–2009Q4), overbuilt shipping capacity (2011Q1–2012Q4), oil price plunge (2016Q1–2017Q3), and COVID-19 pandemic (2020Q1–2020Q4). Further, this study conducted real-time risk analysis to demonstrate how to link forecast scenarios with unconditional real-time forecasts of the real freight rates.

More specifically, this study analyzes the factors that influence economic conditions, by each historical episodes, based on the SVAR model of Kilian (2009). We conducted forecast scenario analysis to identify the influence of the structural shocks on the shipping market by each crisis period, employing the methodologies suggested in Waggoner and Zha (1999), and Baumeister and Kilian (2014). This study is significant as it reveals that the business of the shipping market is influenced by different factors and to a different degree depending on the characteristics of each global financial crisis.

### 3. Methodology

#### 3.1. Structural Vector Autoregressive Model

##### 3.1.1. General Definition

The structural vector autoregressive (SVAR) model, a combination of the time-series analysis and a theoretical approach, is widely used in empirical analysis. It is presented as follows:

$$B_0 y_t = B_1 y_{t-1} + B_2 y_{t-2} + \dots + B_p y_{t-p} + \epsilon_t, \text{ where } \epsilon_t \sim iid(0, I_K). \quad (1)$$

where  $y_t$  is a  $(K \times 1)$  vector composed of endogenous variables and  $B_0$  is an impact multiplier matrix, based on economic theory. As the impact matrix  $B_0$  of the SVAR model is unobservable, researchers use the reduced-form VAR model, as follows:

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \dots + A_p y_{t-p} + u_t. \quad (2)$$

If an invertible matrix  $B_0$  exists, the relationship between Eqs. (1) and (2) can be represented as follows:

$$y_t = B_0^{-1} B_1 y_{t-1} + B_0^{-1} B_2 y_{t-2} + \dots + B_0^{-1} B_p y_{t-p} + B_0^{-1} \epsilon_t.$$

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \dots + A_p y_{t-p} + u_t, \quad (3)$$

where  $A_i = B_0^{-1} B_i$ ,  $u_t = B_0^{-1} \epsilon_t$ .

### 3.1.2. Short-Run Restriction

As seen in Eq. (3), the SVAR model and reduced-form VAR model indicate a relationship, mediated by the impact matrix  $B_0$ . That is, the structural disturbance term  $\epsilon_t$  and fundamental disturbance term  $u_t$  in the SVAR model are determined by the impact matrix  $B_0$ , which is estimated through the variance–covariance matrix of each disturbance term.

$$E(u_t u_t') = B_0^{-1} E(\epsilon_t \epsilon_t') B_0^{-1'} = B_0^{-1} B_0^{-1'} = \Sigma_u, \quad (4)$$

In Eq. (4), the degree of freedom of  $\Sigma_u$  is  $K(K + 1)/2$ , whereas  $B_0$  is a  $(K \times K)$  matrix. Therefore,  $B_0$  should be additionally restrained. The identification of  $B_0$  is mainly based on economic theory. Sims (1980) suggested a short-run restriction to restrain the mutual influence between endogenous variables in a VAR model for a specified amount of time.

Based on the economic theory of  $B_0^{-1}$ , assuming a recursive relationship,  $B_0$  will also have a recursive relationship; the matrix is represented as a lower triangular matrix. Accordingly, the recursive components of  $B_0^{-1}$  can be restored by performing Cholesky decomposition on the variance–covariance matrix  $\Omega$  in the reduced-form VAR model. In this case, the same result will be driven by performing Cholesky decomposition without restraints on  $B_0^{-1}$ , but as the causal relationship is mechanically determined by Cholesky decomposition, a numerical analysis of the relationship between variables is impossible. Thus, it should be made clear that  $B_0^{-1}$  is a recursive relationship based on economic theories and is estimated to have a numerical interpretation. The  $3 \times 3 \Omega$  matrix can be decomposed as follows:

$$hol(\Omega) = PP' = \begin{bmatrix} p_{11} & 0 & 0 \\ p_{21} & p_{22} & 0 \\ p_{31} & p_{32} & p_{33} \end{bmatrix} \begin{bmatrix} p_{11} & 0 & 0 \\ p_{21} & p_{22} & 0 \\ p_{31} & p_{32} & p_{33} \end{bmatrix}'. \quad (5)$$

As the structure obtained through Cholesky decomposition and that of the variance–covariance relationship equation of the reduced-form and structural VAR models are the same,  $B_0^{-1} = P$ , and  $B_0 = P^{-1}$ . Therefore, the error term  $u_t$  estimated as in (10) becomes an orthogonal error term without simultaneous correlation.

$$\begin{bmatrix} u_{1t} \\ u_{2t} \\ u_{3t} \end{bmatrix} = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \\ \epsilon_{3t} \end{bmatrix}. \quad (6)$$

### 3.1.3. Impulse Response Function

The impulse response function dynamically expresses the effect of an unexpected change (shock) in one variable on another variable. It is a tool widely used in the empirical analysis of business fluctuation factors.

Eq. (7) can be obtained by converting the SVAR model into a Vector Moving-Average Model (VMA) to derive the impulse response function.

$$y_t = \sum_{i=0}^{\infty} \Theta_i \epsilon_{t-i}. \quad (7)$$

If the relationship of Eqs. (1) and (2) is applied to Eq. (7), the VMA of the VAR model is represented as follows:

$$y_t = \sum_{i=0}^{\infty} \Phi_i u_{t-i}, \text{ where } \Phi_i = \Theta_i B_0^{-1}. \quad (8)$$

The impulse response function represents the future  $(t + h)$  response of the variable of interest  $y_t^i$  when an impulse occurs in the structural error term  $\epsilon_t$ , and can be expressed as follows:

$$y_{t+h} = \sum_{i=0}^{h-1} \Theta_i \epsilon_{t+h-i}. \quad (9)$$

If  $B_0$  and  $u_t$  are estimated, the response of  $y_t$  components,  $y_t = (y_{1t}, \dots, y_{Kt})'$ , to the shocks of the components of  $\epsilon_t$ ,  $\epsilon_t = (\epsilon_{1t}, \dots, \epsilon_{Kt})'$ , is represented as:

$$\begin{aligned} y_t &= \sum_{i=0}^{\infty} \Phi_i u_{t-i} = \sum_{i=0}^{\infty} \Phi_i B_0^{-1} B_0 u_{t-i} = \sum_{i=0}^{\infty} \Phi_i B_0^{-1} \epsilon_{t-i} = \sum_{i=0}^{\infty} \Theta_i \epsilon_{t-i}, \text{ where } u_{t-i} \\ &= B_0^{-1} \epsilon_{t-i}, \quad \epsilon_{t-i} = B_0 u_{t-i}, \quad \Theta_i \equiv \Phi_i B_0^{-1}. \end{aligned} \quad (10)$$

### 3.1.4. Historical Decomposition

In addition to the impulse response function analysis, the SVAR model can analyze the contribution of each structural shock through forecast error variance decomposition (FEVD) and historical decomposition, depending on the area of interest. FEVD measures the effect of the impact of each variable on the mean squared error (MSE), representing the rate at which the variation of a particular variable is explained by itself and other variables (Hill et al., 2018: 475). Historical decomposition, an expansion of FEVD, shows a cumulative effect of the structural impact of a variable on another variable of interest at a time point  $\tau$ . Historical decomposition enables analysis of the effect of a monetary policy on GDP during a certain period, for example during the Asian financial crisis or the global financial crisis. The effect of the structural impact of the variable  $y_i$ , occurring between the reference time points  $t_0$  and  $\tau$ , on the variable  $y_j$  at time  $\tau$  can be calculated as follows:

$$HD_{i,j,t+\tau} = \sum_{h=0}^{\tau} \frac{\partial y_{i,t+h}}{\partial \omega_{j,t}} \omega_{j,t+\tau-h}. \quad (11)$$

Moreover, the contribution of variable  $y_j$  to the variation of variable  $y_i$  at time  $\tau$  is as follows:

$$contrib(HD_{i,j,t+\tau}) = \frac{HD_{i,j,t+\tau}}{\sum_{j=1}^k HD_{i,j,t+\tau}}, \quad i = 1, 2, \dots, k. \quad (12)$$

### 3.2. Forecast Scenario Analysis

Forecast scenario analysis, which is referred to as conditional forecasting by some researchers, aims to analyze the effect of a variable of interest on an economic impact in a hypothetical scenario. This analysis method is differentiated from the traditional time-series forecast, whose primary purpose is to enhance predictability, as it assumes that the structural shocks of the past occur again and analyzes their effect on the current economy (Kilian & Lütkepohl, 2017:124). Furthermore, forecast scenario analysis has the advantage of being able to analyze the risks of the current economic situation and derive policy implications for risk-response measures by revealing the main driving forces of business cycles (Baumeister & Kilian, 2014:120).

Baumeister and Kilian (2014) identified structural shocks from major events that influenced international crude oil prices through forecast scenario analysis and analyzed the impact of these shocks with the assumption that they would occur again. Similarly, we used the forecast scenario analysis method to analyze the factors affecting economic fluctuations in the shipping market according to major events.

First, impulse response function at time point  $(t + h)$  was estimated.

$$y_{t+h} = \sum_{i=0}^{\infty} \Theta_i \omega_{t+h-i} = \sum_{i=0}^{h-1} \Theta_i \omega_{t+h-i} + \sum_{i=h}^{\infty} \Theta_i \omega_{t+h-i}. \quad (13)$$

The impulse response function at a future time can be expressed as the sum of the cumulative effects of the impulses that have been expressed up to the present  $(t)$  and the cumulative effects of the future that have not yet been expressed. Assuming that the future cumulative

impact is zero for forecast scenario analysis, where setting the cumulative effect of the shock to zero means setting  $\omega_{(t+1)}, \dots, \omega_{(t+h)}$  as zero (0), the current conditional expectation for future structural shocks can be expressed as follows

$$y_{t+h|t} = \sum_{i=h}^{\infty} \Theta_i \omega_{t+h-i}. \quad (14)$$

Forecast scenario setting assumes a hypothetical shock or uses a shock that actually occurred during a crisis as a historical scenario. By applying a shock obtained through historical decomposition, the historical scenario allows us to identify vulnerabilities to potential crises and to obtain information on risk response. When calculating the changes in  $y_{t+h}$  due to the future structural impulse vector  $\{\omega_{t+1}^{scenario}, \dots, \omega_{t+h}^{scenario}\}$ , which is not zero, the conditional expected value at each time point  $h = 1, 2, \dots$  is as follows:

$$\begin{aligned} E\left(\sum_{i=0}^{h-1} \Theta_i \omega_{t+h-i} + \sum_{i=h}^{\infty} \Theta_i \omega_{t+h-i} \mid \{\omega_{t+h-i} = \omega_{t+h-1}^{scenario}\}_{i=0}^{h-1}, \Omega_t\right) - E\left(\sum_{i=0}^{h-1} \Theta_i \omega_{t+h-i}\right) \\ + \sum_{i=h}^{\infty} \Theta_i \omega_{t+h-i} \mid \{\omega_{t+h-i} = \omega_{t+h-1}^{baseline}\}_{i=0}^{h-1}, \Omega_t\} = \sum_{i=0}^{h-1} \Theta_i \omega_{t+h-1}^{scenario}. \end{aligned} \quad (15)$$

In the equation above,  $\Omega_t$  is the set of information at time point  $t$ . When the percentage deviation of  $y_{t+h}$  due to the forecast scenario shock is obtained through Eq. (15), the change in  $y_{t+h}$  due to the scenario is as follows:

$$y_{t+h|t} + \sum_{i=0}^{h-1} \Theta_i \omega_{t+h-i}^{scenario}. \quad (16)$$

## 4. Data and Results

### 4.1. Data

The variables for analysis were set based on the macroeconomic model suggested in Stopford (2009). According to Stopford (2009), the global economic condition such as industrial production affects trade in goods, which determines the supply and demand for ships, which subsequently affect ship prices and freight rates.

In this study, the model was composed of two variables related to the global economy and three variables related to the shipping market. Specifically, we used the CBOE Volatility Index (VIX) as the global economy variable and the global price of Brent crude oil per barrel as the

international oil price. Data were sourced from Federal Reserve Economic Data (FRED). VIX is an index representing the volatility of Standard & Poor (S&P) 500 index options listed on the Chicago Options Exchange, and accounts for the next 30 days; the index has been used in several studies as a proxy variable for macroeconomic uncertainty (Bloom, 2009; Baker et al., 2016). With rising economic uncertainty, economic actors tend to wait and watch, delaying making decisions until the uncertainties are resolved (Bloom, 2009: 624). Uncertainty shock affects both supply and demand in the shipping market; as uncertainty increases, companies delay investment and production, affecting demand, and ship investors delay investment, affecting supply.

Fig. 1 displays a significant increase in the real VIX during the Asian crisis of 1997, the Russian moratorium of 1998, the September 11 attacks in 2001, the IT bubble of 2002, the financial crisis of 2008, the European financial crisis of 2011, the Greek debt crisis of 2015, the oil price instability of 2016, and the COVID-19 pandemic in 2020. Conversely, freight rates in the shipping market exhibited the opposite trend during the same period. During the 1990s to early 2000s, the shipping industry experienced low freight rates, which further declined during the Asian economic crisis, Russian moratorium, and the September 11 attacks. However, as the global boom ignited by China's growth emerged in the mid-2000s, freight rates experienced a sharp rise, in stark contrast to the VIX. When the VIX reached its lowest point during the global financial crisis, shipping market freight rates also reached their lowest point. This pattern has continued to occur since then. Therefore, it is apparent that shipping market freight rates exhibit immediate responsiveness to uncertainty spreading in the global economy. This implies that although there may be an issue in the global economy and no immediate decrease in industrial production and cargo volumes, the shipping market could still be impacted by market anxiety.

International oil prices have been identified as a key factor for global economic instability in the scholarly literature (Kavussanos & Marcoulis, 2000; Grammenos & Arkoulis, 2002; Kilian & Park, 2009; McPhail et al., 2012; Baumeister & Kilian, 2014; Baumeister & Kilian, 2016). Several earlier research studies have identified the global oil price as a crucial factor that has an impact on shipping freight rates (Beenstock & Vergottis, 1989, 1993; Kogan et al., 2009; Lyridis et al., 2014; Papastolou et al., 2014; Gavriilidis et al., 2018; Lim et al., 2019; Michail, 2020).

Shipping-market-related variables were composed of supply and demand in the shipping market and a variable related to freight rates. First, a merchandise trade variable is required as a demand variable. However, for the global merchandise trade, the minimum measurable

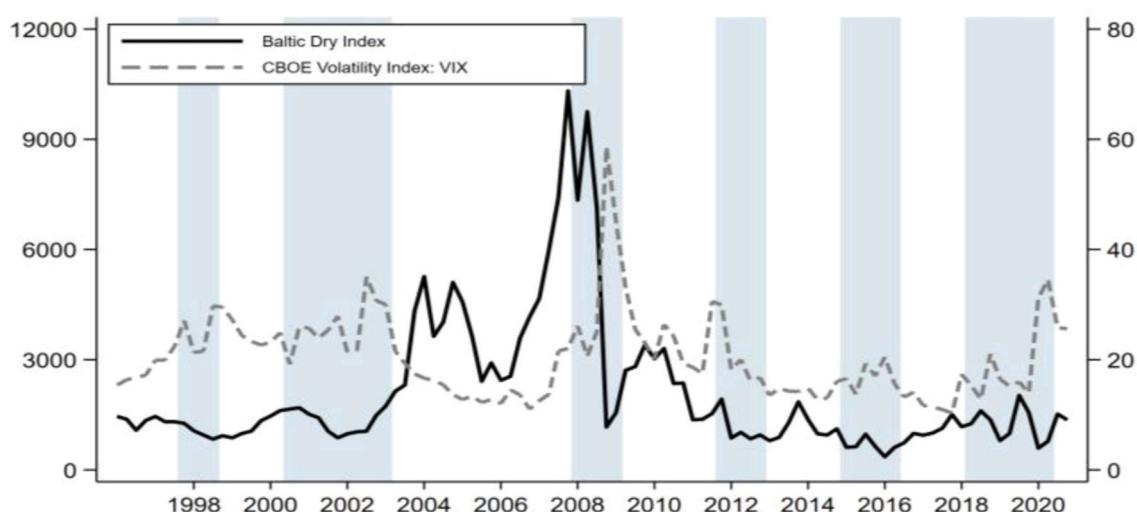


Fig. 1. VIX and BDI.

**Table 1**  
Variables: Description and Source.

Variable	Description	Source
VIX	Chicago Options Exchange Volatility Index	• FRED
OIL	Brent crude oil price	• FRED
TR	IMT	• OECD
FD	World fleet development	• Clarksons Shipping Intelligence Network
BDI	BDI	• Clarksons Shipping Intelligence Network

Note: FRED: Federal Reserve Economic Data

period is a year, which is not suitable for the present study. Instead, the OECD's international merchandise trade statistics (IMTS) were used as a proxy variable for merchandise trade. To secure the data, the exports of G7 countries were used, as they provide the longest time-series data. As a supply variable, global fleet development, provided by Clarksons Shipping Intelligence Network, was used. The global fleet data were available from 2005 Q1, and used the sum of the bulk carriers, containers, and tankers as a proxy variable for the shipping supply. As for the shipping freight rate variable, the BDI, provided by Clarksons Shipping Intelligence Network, was used. BDI, international oil prices, and IMT were converted into real variables using the US Consumer Price Index (CPI).

The analysis period was from 1996 Q1, when the data for all variables were available, to 2020 Q4, when the latest data were available.

Summary statistics of the variables are shown in Table 2.

As shown in Table 3, the unit root test revealed that most of the variables taking the original series and natural logarithms have a unit root. Thus, a stable time-series was obtained by applying Hodrick & Prescott (1997) to the log level variable.

The appropriate lag is determined as the lag that minimizes the Akaike or Schwartz statistic by using the covariance matrix of the estimation error of the SVAR model. In this study, the appropriate time lag of the model was set to 2, in accordance with the Schwarz Bayesian Information Criterion (SBIC).

#### 4.2. Empirical analysis results

##### 4.2.1. Results of recursive structural vector autoregressive model estimation

**4.2.1.1. Results of the reduced-form vector autoregressive model estimation.** Table 5 shows the estimation results for the reduced-form VAR model. The shock effect of all variables on BDI was not statistically significant, but the direction was found to be consistent with the theory. However, the effects of shipping market variables on BDI, including merchandise trade and fleet, produced statistically significant results. Furthermore, macroeconomic variables, such as VIX and oil price, showed statistically significant effects on merchandise trade, which supports the recursive relationship established between variables in this study.

**4.2.1.2. Impulse response analysis results.** The recursive structural VAR

**Table 2**  
Summary Statistics.

Variable	Mean	SD	Unit: [Index, USD, DWT mil.]
VIX	20.31	7.57	
OIL	0.26	0.13	
TR	5.23	0.89	
FD	1064.52	423.41	
BDI	10.29	9.09	
N	100		

**Table 3**  
Augmented Dickey-Fuller Test Results.

Variable	Original Series	Log Level	HP-Filter
VIX	-4.29 * **	-3.68 * **	-12.64 * **
OIL	-1.77	-1.68	-9.69 * **
TR	-1.46	-2.81 * *	-11.78 * **
FL	5.36	1.16	-3.71 * *
BDI	-3.09 * **	-2.9 * *	-11.77 * **

**Table 4**  
Information Criteria.

lag(h)	AIC	HQIC	SBIC
1	40.61	40.67	40.75
2	33.49	33.82*	34.31*
3	33.41*	34.01	34.9
4	33.54	34.41	35.7
5	33.78	34.93	36.63
6	33.67	35.09	37.19

Note: AIC: Akaike Information Criterion; HQIC: Hannan–Quinn information criterion; SBIC: Schwarz Bayesian Information Criterion

**Table 5**  
Results of the Reduced-Form VAR Model Estimation.

VARIABLES	(1) vix	(2) $\Delta oil$	(3) $\Delta tr$	(4) $\Delta fl$	(5) $\Delta bdi$
$vix_{t-1}$	0.78 * ** (0.12)	-0.51 (0.34)	-0.29 * ** (0.11)	0.00 (0.01)	-0.24 (0.41)
$vix_{t-2}$	-0.04 (0.12)	0.89 * ** (0.34)	0.30 * ** (0.11)	0.00 (0.01)	0.10 (0.41)
$\Delta oil_{t-1}$	0.08 (0.05)	0.08 (0.14)	0.06 (0.04)	0.01 * * (0.00)	0.07 (0.17)
$\Delta oil_{t-2}$	0.03 (0.05)	-0.15 (0.14)	-0.01 (0.04)	0.00 (0.00)	0.08 (0.17)
$\Delta tr_{t-1}$	-0.14 (0.15)	0.25 (0.42)	-0.08 (0.13)	-0.02 * * (0.01)	1.10 * * (0.50)
$\Delta tr_{t-2}$	-0.07 (0.17)	0.97 * * (0.47)	-0.08 (0.15)	-0.01 (0.01)	0.35 (0.56)
$\Delta fl_{t-1}$	0.90 (1.17)	-2.41 (3.24)	0.15 (1.02)	0.40 * ** (0.09)	-8.10 * * (3.91)
$\Delta fl_{t-2}$	-1.21 (1.19)	2.00 (3.31)	0.40 (1.04)	0.48 * ** (0.09)	2.66 (4.00)
$\Delta bdi_{t-1}$	-0.01 (0.03)	-0.04 (0.09)	0.06 * * (0.03)	0.00 (0.00)	-0.02 (0.11)
$\Delta bdi_{t-2}$	0.07 * * (0.03)	-0.16 * (0.09)	-0.03 (0.03)	0.00 (0.00)	-0.21 * * (0.11)
Obs.	97	97	97	97	97

Note: The number in parentheses () are the standard error. \* \* \* p < 0.01, \* \* p < 0.05, \* p < 0.1

model was estimated based on the exogeneity between variables in the macroeconomic shipping model, as suggested by Stopford (2009). As for the order of variables, VIX, representing global economic uncertainty, was the most exogenous variable, followed by oil price. VIX was used as a leading indicator of the global economy, which was assumed to be influenced by VIX and oil price shocks at the time. This in turn was assumed to influence IMT, which would then affect fleet development and, subsequently, BDI.

In this study, the impulse response functions of BDI to VIX, international oil price, merchandise trade, and global fleet development shocks were analyzed. The impulse response function can dynamically observe the movement of other variables constituting the model when an unexpected shock occurs to the endogenous variable. Fig. 1 shows the impulse response function of each variable for each variable shock. In the figure, the blue-shaded part represents the 1-standard deviation confidence interval, and the red line is the impulse response function estimated through the model. The Y-axis represents the percentage change, and the X-axis, the monthly forecast clock. The confidence interval is based on Gonçalves and Kilian's (2004) recursive-design wild

bootstrap with 2000 replications.

The results that estimated responses lie within the confidence interval for most of the forecast horizons suggest the shock of each variable has a significant impact on the freight rates. We observed the response of shipping market freight rates by variable. In response to VIX shock, the freight rates decreased immediately, but the effect gradually disappeared. The international oil price shock immediately raised freight rates, and later, the effect gradually decreased; then, however, from the 6th quarter onward, there was a statistically significant decrease. According to the analysis, the impact of merchandise trade also initially increased freight rates, but this effect gradually disappeared. Conversely, the fleet development shock was found to slightly, non-significantly increase freight rates in the short term; however, the rate decreased significantly from the fourth quarter onwards.

In the impulse response analysis between each variable in this study,

the directions of the recursive relationship between the variables were set based on Stopford (2009). The results are in line with the theoretical predictions: oil price and merchandise trade shocks trigger an increase in freight rates, while VIX and fleet shocks decrease freight rate in the medium-run, indicating that the model established in this study was suitable.

**4.2.1.3. Results of historical decomposition.** Historical decomposition is a cumulative estimation of the impact of past and present factor-specific shocks on current dry freight rates using the cumulative SVAR model, making it easy to see the continued process of impulse response function over time, instead of only at a certain time.

The change in dry freight rates according to the shock of each factor appears as positive (+) when it causes an increase in freight rates and as a negative (-) when it causes a decrease. Fig. 2 shows the historical factor

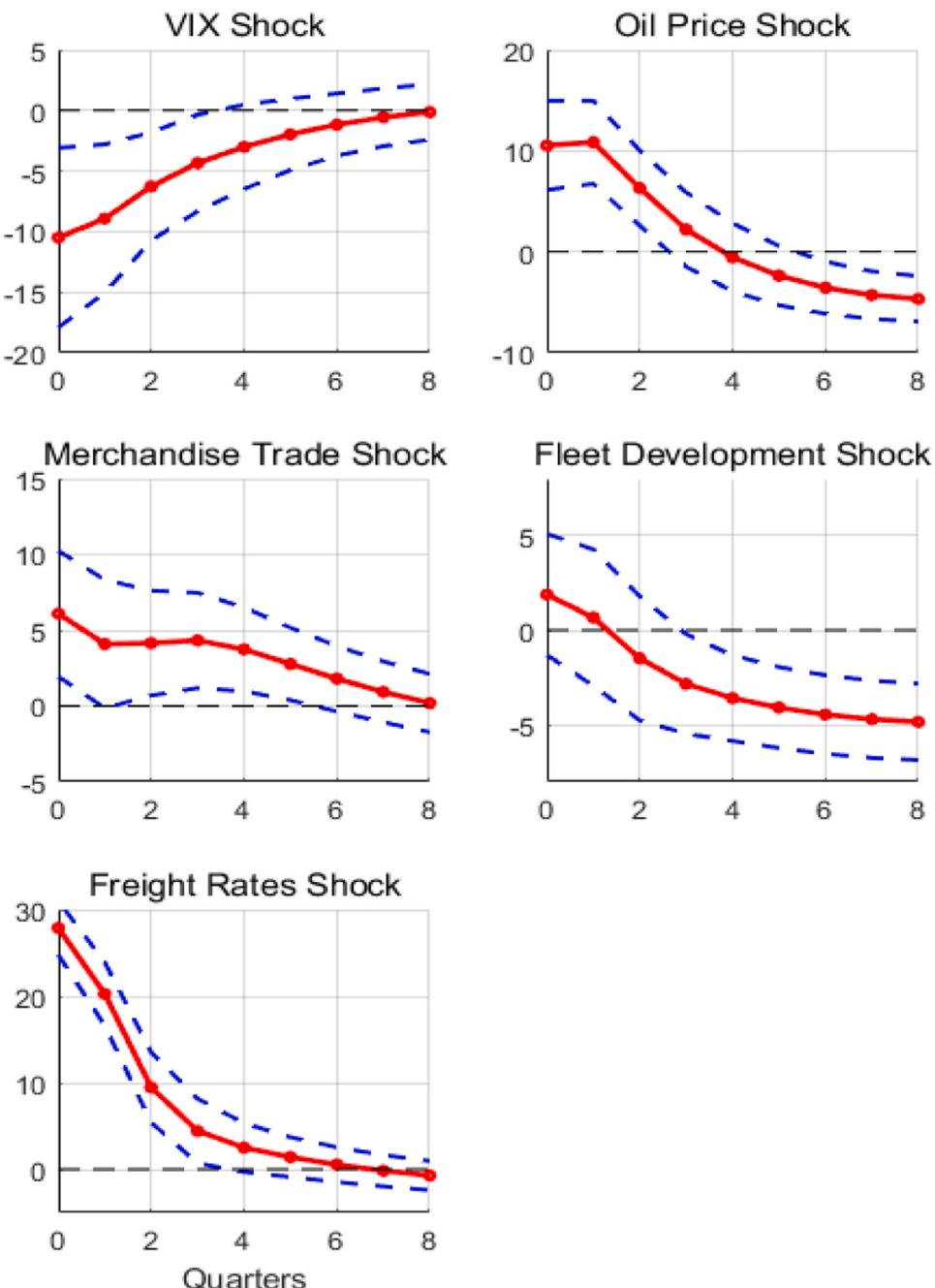


Fig. 2. Freight Rates Impulse Response Function.

decomposition of this study.

Among the periods established in this study as having great influences on the shipping market, the Asian financial crisis between 1997 and 1999 had less global impact than the other crises. The shipping market at that time seems to have been influenced mainly by VIX and international oil price shocks.

From 2006, when a boom phase started in the global economy, including the shipping market (driven by the economic growth of China, its entry into the WTO, and globalization) until the global financial crisis, the market was influenced by various macroeconomic variables, but mostly by freight rate shock. This seems to be because anxiety over freight rate increases is reflected in the market, as supply-side fleet development does not immediately respond to increase in demand-side merchandise trade, thereby overheating the shipping market.

Unlike the Asian financial crisis, which affected only some Asian countries, the global financial crisis of 2008–2009 (which originated in the United States and was accelerated by the Lehman Brothers crisis) was an economic crisis that started in the financial sector and transferred to the real economy. This led to a global recession. Consequently, production and trade decreased, and in the shipping market, supply and demand for fleet development dampened due to a sharp drop in seaborne merchant trade during 2009, shrinking the global shipping market. Furthermore, through historical decomposition we found that the shipping market freight rates were affected by VIX and merchandise trade shocks during the global financial crisis from 2008 to 2009.

In 2011, large orders of ships poured into the shipping market due to the expectation of a continuous increase in freight rates prior to the global financial crisis, creating the problem of oversupply of ships. Since then, the fleet development (supply) shock has been pushing shipping market freight rates downward. The market condition deteriorated due to a drop in profitability in the shipping industry, causing a shortage of liquidity, leading to bankruptcies and restructuring of shipping companies. This further accelerated the recession in the industry.

From 2016 to 2017, international oil price was the main influencing factor when BDI recorded an all-time low due to global economic instability, with a fall in oil prices caused by increased production of US shale oil and a second round of ship oversupply. A fall in oil price may improve profits of shipping companies in an economic boom, but generates additional downward pressure on freight rates during a recession, when shipping companies' bargaining power with shippers weakens. In addition, a big decrease in oil prices due to international frictions seem to have raised uncertainty in the world economy, negatively affecting global shipping demand and freight rates.

During the COVID-19 crisis, from 2020 to the present, VIX and merchandise trade shocks had the biggest impact, as the crisis was ignited by the outbreak of the pandemic and not by economic problems and affected the economic sectors. However, unlike other periods, we are witnessing a fast economic recovery. This result is consistent with the rapid increase in the stock index—considered a leading indicator of the global economy—and CCFI, despite the earlier prospect of the COVID-19 pandemic's triggering the worst recession in history.

Fig. 3 shows the contribution of each factor to the change in freight rates and the movement of BDI at each time. For convenience of interpretation, BDI, substantiated through CPI, was standardized as of 2020 Q4. In 2007 Q4, when freight rates peaked, the contribution of freight rates themselves was the highest at 58.96%.

The expectation of a continuous increase in freight rates during this period may have caused a surge in freight rates. In addition, in 2016 Q1, when freight rates were the lowest, the contribution of self-impact was 32.27%; contrarily, in 2007 Q4, when freight rates were the highest, extreme concern about the decline in freight rates may have caused an actual decline in freight rates. In short, at historic high and low points, freight rates seem to be determined by the overheatedness of a rise or fall, rather than by the normal supply and demand in the market.

Contribution rates of shocks by factor influencing shipping freight rates during the periods of main events are discussed under the results

for cumulative historical decomposition to identify the contribution of each factor by period. Historical episodes were divided into the Asian financial crisis (1997 Q3–1999 Q4), shipping market boom (2006 Q3–2008 Q2), global financial crisis (2008 Q3–2009 Q4), the period of European fiscal crisis and oversupply of the shipping market (2011 Q1–2012 Q4), international oil price plunge (2016 Q1–2017 Q3), and the COVID-19 pandemic (2020 Q1–2020 Q4).

Fig. 4 shows how the fluctuations in freight rates can be explained by the shocks of each factor over the aforementioned periods, and not at a single point in time. In the case of the Asian financial crisis, international oil price shocks, merchandise trade shocks, and VIX shocks were found to be major factors for the fluctuation of freight rates. During the shipping market boom and global financial crisis, the contribution of freight rates themselves was the highest, followed by the shocks of international oil prices, VIX, and merchandise trade. The fluctuations at that time can thus be interpreted as a phenomenon caused by the overheated market, when freight rates reach highs and lows, as shown in the analysis results for each point in the previous section.

The oversupply period also showed the highest contribution rate of the freight rates themselves, but the contribution of the fleet development shock was higher than for other periods. This trend provided empirical evidence that the major factor in the fluctuation of the freight rates was oversupply. During the oil price plunge, international oil price shock made the highest contribution. During the COVID-19 period, the contribution rate of VIX shock to freight rate shock was the second-highest. This means that market anxiety played a bigger role than recession in the real economy.

There are many existing qualitative discussions of developments, causes, and trends in the shipping market during the major analysis periods of this study. However, to the best of our knowledge, no studies have found and compared the major factors that have influenced the shipping market by period. This study is different from previous ones because it both presents quantitative evidence and conducts a qualitative analysis on the major periods that have influenced the shipping market.

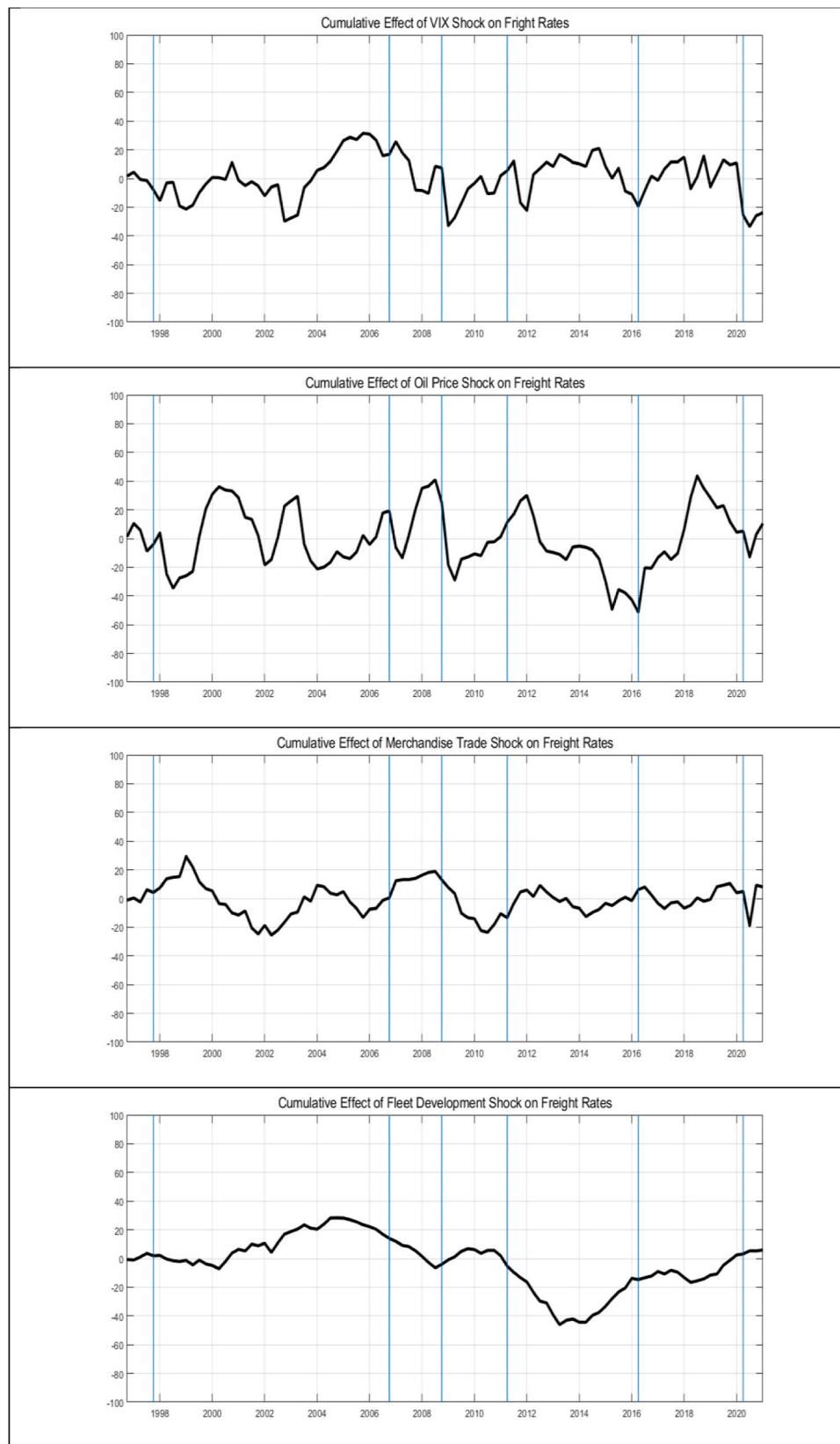
#### 4.2.2. Forecast scenario analysis results

**4.2.2.1. Forecast scenario.** Forecast scenario analysis measures potential vulnerability to specific events influencing the economy. It is a similar method to the stress test, because it performs a simulation analysis under the assumption that exceptional but plausible incidents will occur again.

For a forecast scenario analysis, historical and hypothetical scenarios are used; a historical scenario is created by applying changes in real variables during a major economic crisis, while a hypothetical scenario is created arbitrarily by assuming the movement of variables. In this study, we used the historical scenarios of six major events where macroeconomic shocks influenced the shipping market. As aforementioned, the analysis period was divided into the Asian financial crisis (1997 Q3–1999 Q4), market boom (2006 Q3–2008 Q2), global financial crisis (2008 Q3–2009 Q4), oversupply (2011 Q1–2012 Q4), oil price plunge (2016 Q1–2017 Q3), and COVID-19 pandemic (2020 Q1–2020 Q4).

Fig. 5 shows the forecast scenarios by period. Each scenario shows the forecast and the difference between the forecast and the baseline in percentage. In other words, the figure represents the change in freight rates with each forecast scenario.

**4.2.2.2. Forecast scenario analysis results.** The forecast scenario analysis reveals the dynamic differences in the forecasts of freight rates when the previously set scenario is reproduced at the current time point. This approach has the advantage of being able to forecast the transmission channel of each shock separately when an event similar to a specific crisis in the past occurs in the present. This allows conditional forecasts to be completely different from forecasts performed by simply



**Fig. 3.** Historical Decomposition of the Baltic Exchange Dry Index.

considering the time-series data.

Fig. 6 shows the result of forecast scenario analysis from 2020 Q4 in real time. In the figure, the solid black line represents the model-based forecast in the case of no shock, calculated through reduced-form VAR

(2). The colored lines are forecast values that have been estimated by assuming that the major events in this study occurred during 2020 Q4. For analysis, BDI was converted and analyzed as of 2020 Q4.

In the case of the Asian financial crisis scenario, the freight rates

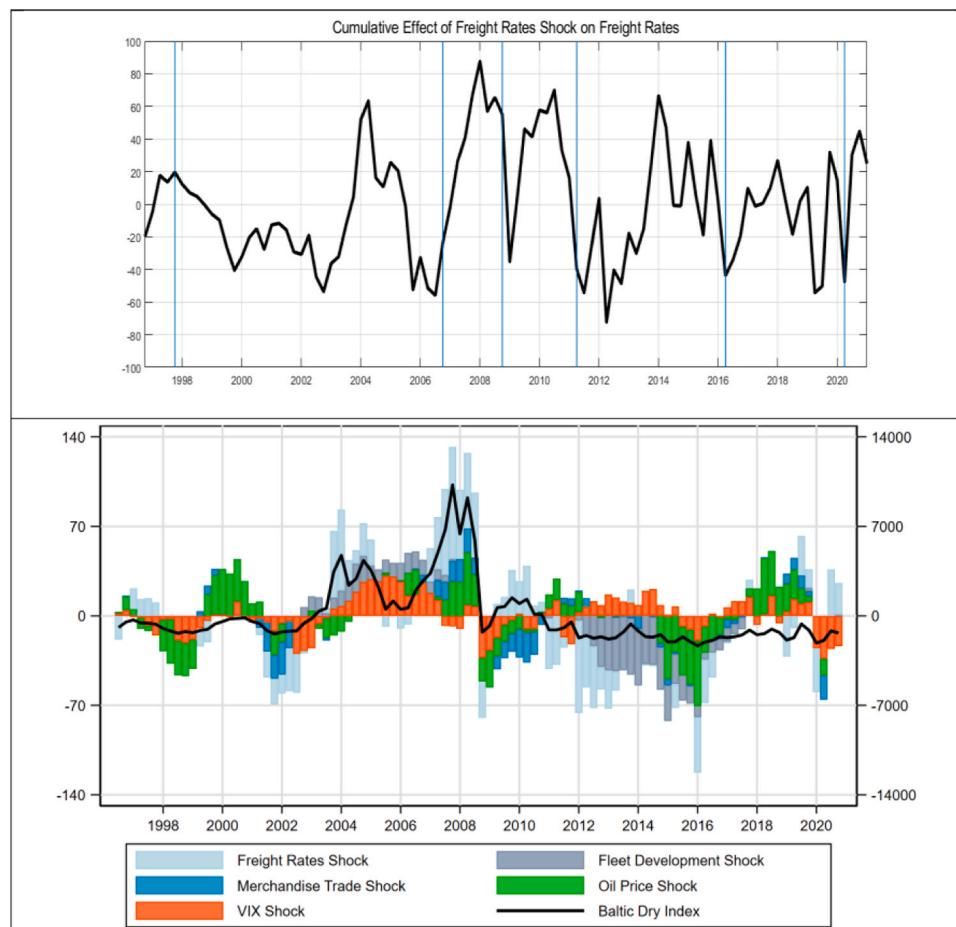


Fig. 3. (continued).

forecast does deviate significantly from the baseline about a year later. In the case of the shipping market boom scenario, freight rates are forecast to drop slightly for a short period and then quickly exceed the baseline. In the case of the international oil price shock scenario, it does not appear to deviate significantly from the baseline.

In the case of the global financial crisis and COVID-19 scenarios, which greatly affected the whole world, freight rates were forecast to make a sharp fall and then move towards recovery. According to the prediction, freight rates under COVID-19 will show a much faster recovery than under the global financial crisis. This is a result consistent with the real rapid recovery of the global economy and shipping market after a sharp decline in the early stages of the COVID-19 outbreak..

These results seem to occur because in the case of the global financial crisis, the economic problems that occurred in the financial sector rapidly transferred to the real economy. This resulted in a long-term economic recession, from which the shipping market recovered only after a long time. Unlike the global financial crisis, the COVID-19 pandemic has the characteristics of a natural disaster—an epidemic outbreak—and we did not observe a collapse or recession in the real economy, due to the active quarantine measures, vaccination, and other preemptive economic stimulus measures of governments globally, despite the worries of experts.

The results are similar in the sensitivity analysis of the global financial crisis and COVID-19 pandemic scenarios. During the global financial crisis, the recovery of the merchandise trade was slow as VIX and oil prices rose, making economic activity contract due to increased uncertainty and reduced production due to cost increases. In contrast, the COVID-19 pandemic scenario showed a continued increase in uncertainty, but a faster recovery in the real economy, including oil price

and merchandise trade. Compared to the case of global financial crisis, the COVID-19 pandemic scenario also allowed the shipping market to make a quick recovery..

## 5. Conclusion

In this study, we conducted an empirical analysis using a structural VAR model to identify the major causes of economic fluctuations during the historical episodes in the shipping market. As global macroeconomic variables, VIX, Brent crude oil price, IMT, world fleet, and BDI were used; global fleet development and BDI were used as shipping market variables. Observing the response of shipping market freight rates to shocks by variable, the freight rates decreased immediately, but the effect gradually disappeared in response to the VIX shock. The international oil price shock immediately raised freight rates, and subsequently, the effect gradually decreased. However, from the sixth quarter onward, rates decreased at a significant rate. The impact of merchandise trade also initially increased freight rates, but the effect again gradually disappeared. Conversely, fleet development shock was found to slightly increase freight rates in the short term, and the rate of increase was not statistically significant. However, they then decreased statistically from the fourth quarter onward.

In the historical decomposition analysis, divided into financial crisis periods, it was found that shipping market freight rates were affected by VIX and oil price shocks during the Asian crisis and by VIX and merchandise trade shocks during the global financial crisis from 2008 to 2009. Since 2011, fleet development (supply) shock has been pressuring shipping market freight rates. From 2016 to 2017, it was found that international oil price was the main influencing factor, when BDI

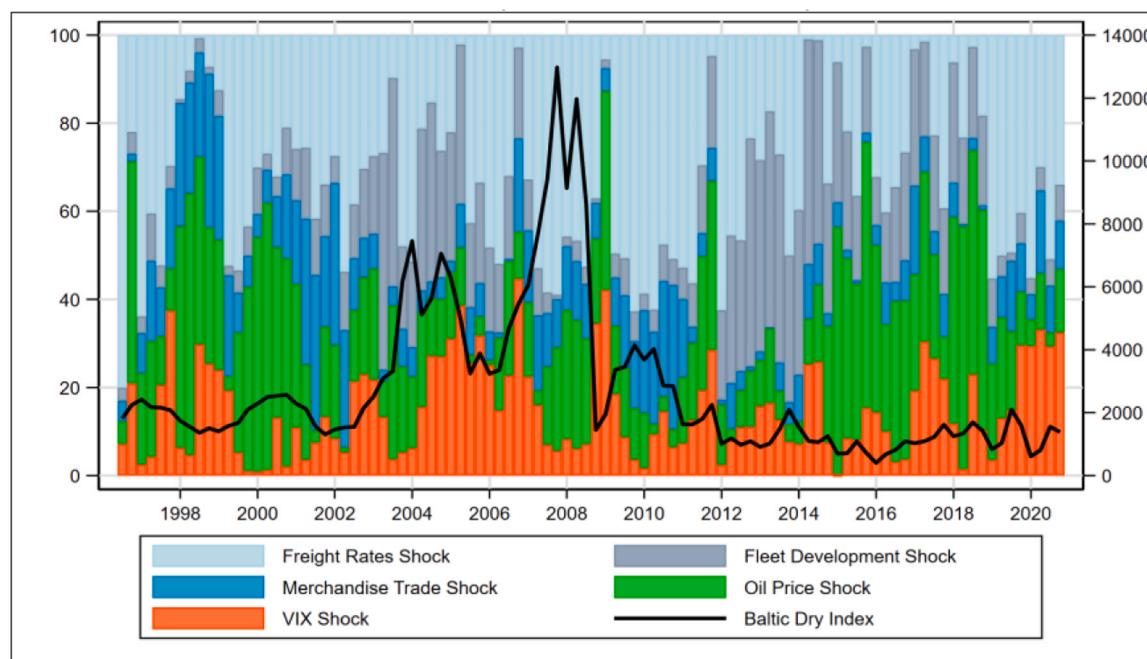


Fig. 4. Contribution Rates of Shocks by Factor to Baltic Dry Index Fluctuations at Each Time.

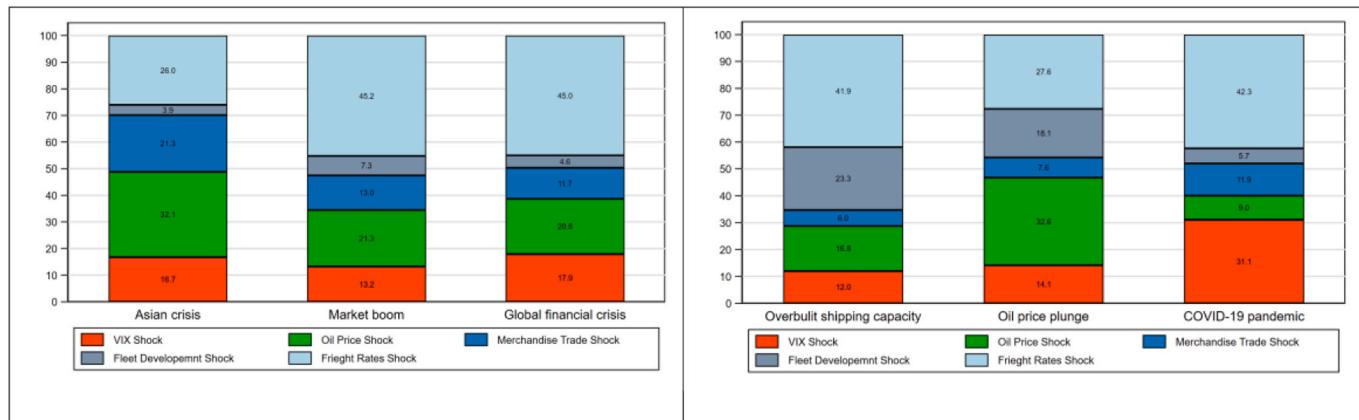


Fig. 5. Contribution Rates of Shocks by Factor to Baltic Dry Index Fluctuations in Each Period.

recorded an all-time low due to global economic instability, with a fall in oil prices caused by increased production of US shale oil and a second round of oversupply of ships. During the COVID-19 pandemic from 2020 to the present, VIX and merchandise trade shocks had the biggest impact, as the crisis affecting the shipping market was ignited by the outbreak of the pandemic and not by economic problems. However, unlike other periods, the economy has been recovering quickly.

This result can be found in the factor analysis by period including the COVID-19 pandemic, where the contribution rate of VIX shock was the fastest, except for that of the shock of freight rates themselves. This means that market anxiety, rather than real economic recession, affected the shipping market more significantly.

The results of forecast scenario analysis, which was conducted under the assumption that the shocks during the individual episodes repeat over time, shows that the freight rates were forecast to fall immediately and recover during the global financial crisis and the COVID-19 pandemic. However, the pace of recovery was found to be faster in the latter period than in the former. As mentioned earlier, this result is consistent with the fast recovery from recession in the real economic

activities and shipping market at the early stage of the COVID-19 pandemic.

This study expects to contribute the literature by investigating the economic impacts of historical events. Our findings suggest that each crisis differs in causes, transition process, influence, and time taken for recovery, and has distinct effects on the shipping industry. The results will be of interest to market participants by helping them understand the economic environment better and formulate risk management strategies accordingly. Besides its contributions, the model established in this study has some limitations. First, as we have experienced limited number of historical events, and the characteristics of each event are different, the model may lose explanatory power for events that occur due to structural changes in the economy. This limitation can be overcome by discovering new factors through market monitoring in the future. Second, this model does not consider the influence of historical events on individual firms or banks, as we perform analysis at the macroeconomic level. In future research, it will be fruitful to examine the effects of historical events at the micro level by using stress test or default prediction analysis.

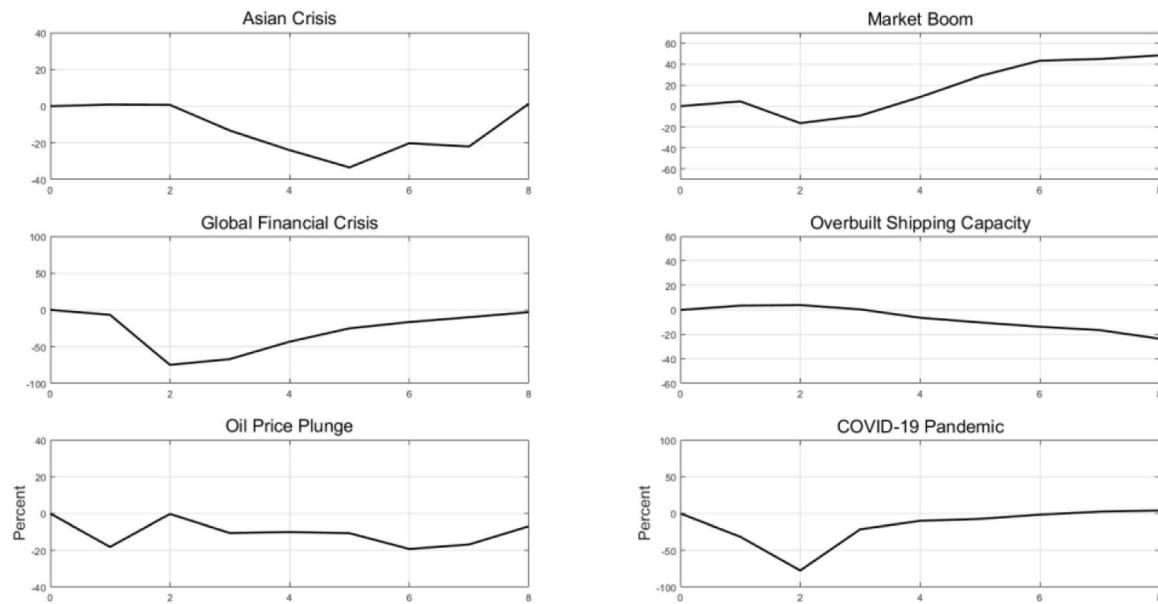


Fig. 6. Forecast Scenarios by Period.

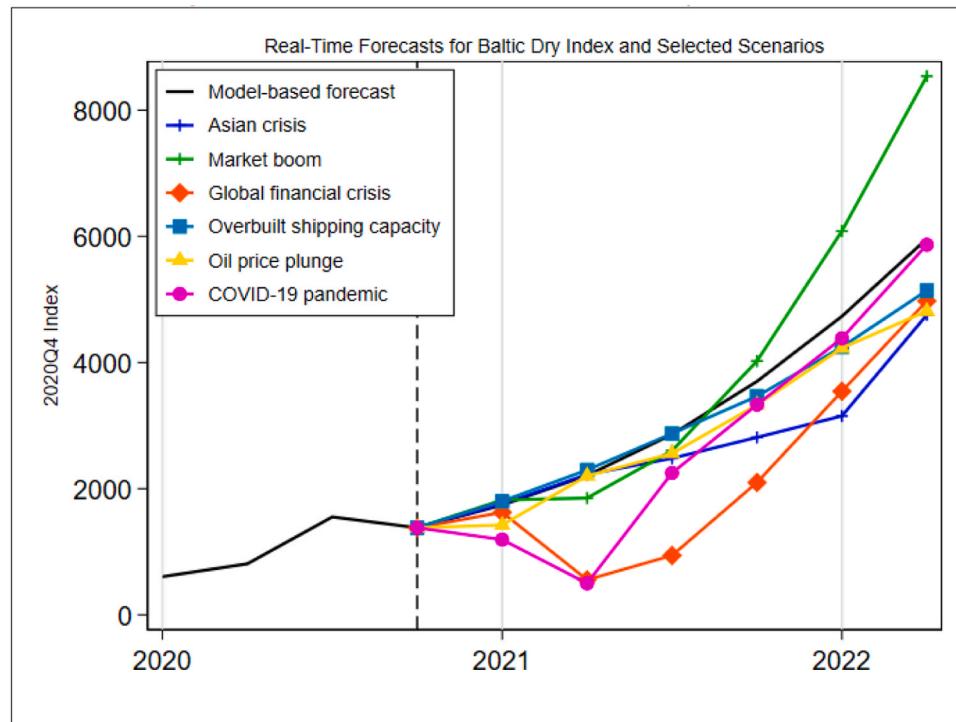


Fig. 7. Real-time Forecast Scenario Analysis Result.

In conclusion, individual global financial crises differ in cause, transition process, influence, and time taken for recovery. Thus, when another global financial crisis occurs, the shipping market may respond to it with novelty, requiring response strategies appropriate to each new crisis, at the company and national levels. During the worldwide economic downturn, many shipping companies underwent multiple bankruptcies or government-led restructurings. While the economic shocks from the pandemic were unprecedented, they have provided insight into various types of economic shocks. It is beyond dispute that the shipping industry is deeply intertwined with the global economy. In this study, we develop a model to forecast shipping market freight rates under various

macroeconomic events. Our model predicts the changes in freight rates during normal economic conditions and during times of crisis. Moreover, we observe that the financial solvency of individual companies affects their response to identical macroeconomic circumstances. Hence, it is imperative to devise policies by developing a model that scrutinises the influence of individual enterprises on top of the impact of macroeconomic shifts in the domestic shipping market. Additionally, this research examines solely macroeconomic aspects. Therefore, future studies should integrate port vessel statistics to examine the supply chain perspective.

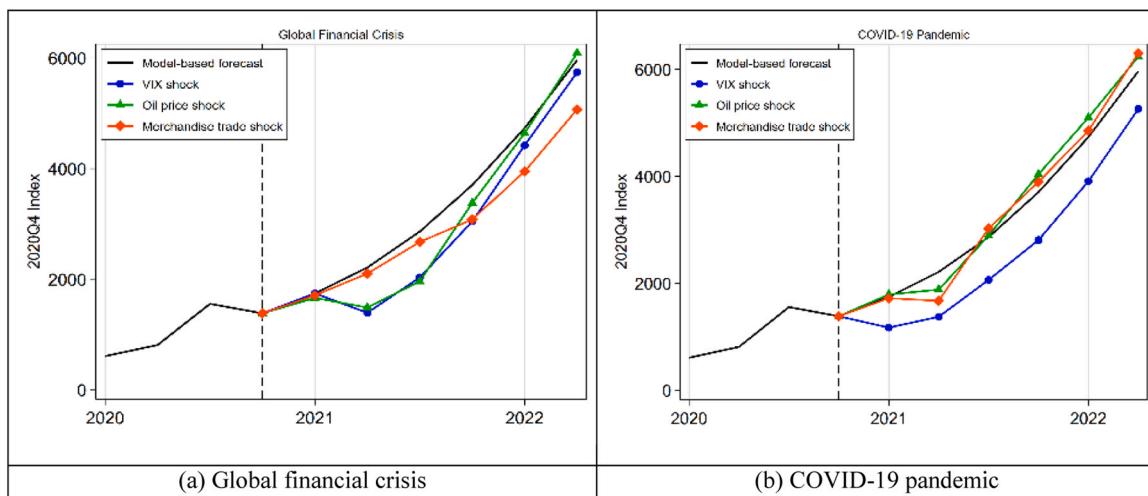


Fig. 8. Sensitivity Analysis of the Global Financial Crisis and COVID-19 Scenarios.

## Funding

This research was supported by the Korea Maritime Institute (grant number BP2021-17). The funding agency had no role in study design; in the collection, analysis and interpretation of data; in the writing of the report; and in the decision to submit the article for publication.

## CRediT authorship contribution statement

**Sunghwa Park** (Conceptualization; Data curation; Formal analysis; Funding acquisition; Investigation; Methodology; Project administration; Resources; Software; Validation; Visualization; Writing - original draft; Writing - review & editing). **Janghan Kwon** (Data curation; Formal analysis; Supervision; Methodology; Resources; Software; Validation; Visualization; Writing - original draft; Writing - review & editing). **Hanna Kim** (Project administration; Investigation; Resources; Visualization; Writing - original draft; Writing - review & editing). **Heeyoung Ryu** (Project administration; Investigation; Resources; Visualization; Writing - original draft; Writing - review & editing). **Taeil Kim** (Conceptualization; Investigation; Methodology; Project administration; Resources; Validation; Writing - review & editing).

## Acknowledgments

This study is a revised and expanded version of “The Global Economic Crisis and the Shipping Industry” supported by Korea Maritime Institute [grant number: GP2021-17].

## Declaration of interest

None.

## Detailed disclosures

None.

## References

Bai, X., & Lam, J. S. L. (2019). An integrated analysis of interrelationships within the very large gas carrier (VLGC) shipping market. *Maritime Economics and Logistics*, 21, 372–389. <https://doi.org/10.1057/s41278-017-0087-3>

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131, 1593–1636. <https://doi.org/10.1093/qje/qjw024>

Baumeister, C., & Kilian, L. (2014). Real-time analysis of oil price risks using forecast scenarios. *IMF Economic Review*, 62, 119–145. <https://doi.org/10.1057/imfer.2014.1>

Baumeister, C., & Kilian, L. (2016). Forty years of oil price fluctuations: Why the price of oil may still surprise us. *The Journal of Economic Perspectives*, 30(1), 139–160. <https://doi.org/10.1257/jep.30.1.139>

Beenstock, M., & Vergottis, A. (1989). An econometric model of the world market for dry cargo freight and shipping. *Applied Economics*, 21, 339–356. <https://doi.org/10.1080/758522551>

Beenstock, M., & Vergottis, A. (1993). *Econometric Modelling of World Shipping*. London: Chapman & Hall.

Bildirici, M. E., Kayıkçı, F., & Onat, I. (2015). Baltic Dry Index as a major economic policy indicator: The relationship with economic growth. *Procedia - Social and Behavioral Sciences*, 210, 416–424. <https://doi.org/10.1016/j.sbspro.2015.11.389>

Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica*, 77, 623–685.

Chen, Z., Zhang, X., & Chai, J. (2021). The dynamic impacts of the global shipping market under the background of oil price fluctuations and emergencies. *Complexity*, 2021(Special issue), 1–13. <https://doi.org/10.1155/2021/8826253>

Dikos, G., Marcus, H. S., Papadatos, M. P., & Papakonstantinou, V. (2006). Niver lines: a system-dynamics approach to tanker freight modeling. *Interfaces*, 36, 326–341. <https://doi.org/10.1287/inte.1060.0218>

Gavriilidis, K., Kambouridis, D. S., Tsakou, K., & Tsouknidis, D. A. (2018). Volatility forecasting across tanker freight rates: The role of oil price shocks. *Transportation Research Part E*, 118, 376–391. <https://doi.org/10.2139/ssrn.3332262>

Ghiorghie, B., & Gianina, C. (2013). The causality relationship between the dry bulk market and worldwide economic growth. *Ovidius Univ Ann Econ Sci States*, 13, 2–6.

Gonçalves, S., & Kilian, L. (2004). Bootstrapping autoregressions with conditional heteroskedasticity of unknown form. *Journal of Economics*, 123, 89–120. <https://doi.org/10.1016/j.jeconom.2003.10.030>

Grammenos, C. T., & Arkoulis, A. G. (2002). Macroeconomic factors and international shipping stock returns. *International Journal of Maritime Economics*, 4, 81–99. <https://doi.org/10.1057/palgrave.ijme.9100033>

Gu, Y., Dong, X., & Chen, Z. (2020). The relation between the international and China shipping markets. *Research in Transportation Business and Management*, 34, Article 100427.

Hill, R. C., Griffiths, W. E., & Lim, G. C. (2018). *Principles of Econometrics*. John Wiley & Sons.

Hodrick, R. J., & Prescott, E. C. (1997). Postwar US business cycles: an empirical investigation. *Journal of Money, Credit, and Banking*, 1–16.

International monetary Policy. ([https://www.imf.org/external/datamapper/NG\\_DP\\_RPCH/@WEO/WEOORLD/KOR/JPN/DEU/FRA/CHN/ITA/ESP/USA](https://www.imf.org/external/datamapper/NG_DP_RPCH/@WEO/WEOORLD/KOR/JPN/DEU/FRA/CHN/ITA/ESP/USA)) (Retrieved on: September 3, 2021).

Jiang, B., Li, J., & Gong, C. (2018). Maritime shipping and export trade on “Maritime Silk Road”. *The Asian Journal of Shipping and Logistics*, 34, 83–90. <https://doi.org/10.1016/j.ajsl.2018.06.005>

Kavussanos, M. G., & Marcoulis, S. N. (2000). The stock market perception of industry risk and macroeconomic factors: The case of the US water and other transportation stocks. *International Journal of Maritime Economics*, 2, 235–256. <https://doi.org/10.1057/palgrave.ijme.2000.19>

Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review*, 99, 1053–1069. <https://doi.org/10.1257/aer.99.3.1053>

Kilian, L., & Park, C. (2009). The impact of oil price shocks on the U.S. stock market. *International Economic Review*, 50(4), 1267–1287. <https://doi.org/10.1111/j.1468-2354.2009.00568.x>

Kilian, L., & Lütkepohl, H. (2017). *Structural Vector Autoregressive Analysis*. Cambridge University Press.

Klovland, J.T., 2002. Business cycles, commodity prices and shipping freight rates: Some evidence from the pre-WWI period. Workshop on Market Performance and the Welfare Gains of Market Integration in History. SNF. ([https://openaccess.nhh.no/nhh-xmlui/bitstream/handle/11250/165223/R48\\_02.pdf?sequence=1](https://openaccess.nhh.no/nhh-xmlui/bitstream/handle/11250/165223/R48_02.pdf?sequence=1)).

Kogan, L., Livdan, D., & Yaron, A. (2009). Oil futures prices in a production economy with investment constraints. *The Journal of Finance*, 64, 1345–1375. <https://doi.org/10.1111/j.1540-6261.2009.01466.x>

Korea Maritime Institute, press release. KMI. Results of a Survey on the Impact of COVID-19 on Shipping Companies (Published on: April 2, 2020).

Kutin, N., Moussa, Z., Vallée, T., 2018. Factors behind the Freight Rates in the Liner Shipping Industry.

Lim, K. G., Nomikos, N. K., & Yap, N. (2019). Understanding the fundamentals of freight markets volatility. *Transportation Research Part E*, 130, 1–15.

Lyridis, D. V., Manos, N. D., & Zacharioudakis, P. G. (2014). Modeling the dry bulk shipping market using macroeconomic factors in addition to shipping market parameters via artificial neural networks. *International Journal of Transport Economics Rivista Internazionale Economia Tras.*, XLI, 231–254.

McPhail, L. L., Du, X., & Muhammad, A. (2012). Disentangling corn price volatility: The role of global demand, speculation, and energy. *Journal of Agricultural and Applied Economics*, 44(3), 401–410. <https://doi.org/10.1017/S10740708000050X>

Michail, N. A. (2020). World economic growth and seaborne merchandise trade: Quantifying the relationship. *Transp Res Interdiscip Perspect*, 4, Article 100108. <https://doi.org/10.1016/j.trip.2020.100108>

Michail, N. A., & Melas, K. D. (2020). Shipping markets in turmoil: An analysis of the COVID-19 outbreak and its implications. *Transportation Research Interdisciplinary Perspectives*, 7, Article 100178. <https://doi.org/10.1016/j.trip.2020.100178>

Nomikos, N. K., & Tsouknidis, D. A. (2022). Disentangling demand and supply shocks in the shipping freight market: their impact on shipping investments. *Maritime Policy & Management*, 1–19. <https://doi.org/10.1080/03088839.2021.2017041>

Papapostolou, N. C., Nomikos, N. K., Pouliasis, P. K., & Kyriakou, I. (2014). Investor sentiment for real assets: The case of dry bulk shipping market. *Review of Finance*, 18, 1507–1539. <https://doi.org/10.1093/rof/rft037>

Park, S., Kwon, J., & Kim, T. (2021). An analysis of the dynamic relationship between the global macroeconomy and shipping and shipbuilding industries. *Sustainability*, 13, 13982. <https://doi.org/10.3390/su132413982>

Park, S., Kim, H., & Kwon, J. (2023). The impacts of demand and supply shocks in the dry bulk shipping market. *The Asian Journal of Shipping and Logistics*, 39(1), 13–22.

Población, J., & Serna, G. (2018). A common long-term trend for bulk shipping prices. *Marit Econ Logist*, 20, 421–432. <https://doi.org/10.1057/s41278-017-0065-9>

Scarsi, R. (2007). The bulk shipping business: Market cycles and shipowners' biases. *Marit Policy Manag*, 34, 577–590. <https://doi.org/10.1080/03088830701695305>

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica*, 48, 1–48.

Stopford, M. (2009). *Maritime Economics* (third ed.). New York: Routledge.

Syriopoulos, T., & Roumpis, E. (2009). Dynamic correlations and volatility effects in the Balkan equity markets. *Journal of International Financial Markets, Institutions & Money*, 19, 565–587. <https://doi.org/10.1016/j.intfin.2008.08.002>

Tsioumas, V., & Papadimitriou, S. (2018). The dynamic relationship between freight markets and commodity prices revealed. *Maritime Economics & Logistics*, 20, 267–279. <https://doi.org/10.1057/s41278-016-00050>

Tsioumas, V., Smirlis, Y., & Papadimitriou, S. (2021). Capturing the impact of economic forces on the dry bulk freight market. *Maritime Transport Research*, 2, Article 100018. <https://doi.org/10.1016/j.marta.2021.100018>

Tsouknidis, D. A. (2016). Dynamic volatility spillovers across shipping freight markets. *Transportation Research Part E*, 91, 90–111. <https://doi.org/10.2139/ssrn.2759851>

Waggoner, D. F., & Zha, T. (1999). Conditional forecasts in dynamic multivariate models. *The Review of Economics and Statistics*, 81, 639–651.

Wu, C. Y., Chou, H. C., & Liu, C. L. (2021). Fear index and freight rates in dry-bulk shipping markets. *Applied Economics*, 53, 1235–1248. <https://doi.org/10.1080/00036846.2020.1827140>

Yin, J., Luo, M., & Fan, L. (2017). Dynamics and interactions between spot and forward freights in the dry bulk shipping market. *Maritime Policy & Management*, 44, 271–288. <https://doi.org/10.1080/03088839.2016.1253884>