

Spectral analysis of the dry bulk shipping market by utilizing the system dynamics approach

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Abstract

Purpose – This research analyzes the cycle of the dry bulk shipping market (DBSM) as a representative of spot and period charter rates in dry bulk shipping to develop strategies for investment timing (i.e. asset play) and fleet trading (chartering strategy).

Design/methodology/approach – Spectral analysis is a numerical approach to extract significant cyclicity, which may be utilized to develop trading strategies. Instead of working with a single dataset (univariate), a system approach can be utilized to observe a significant shipping market cycle in its multivariate circumstance. In this paper, a system dynamics design is employed to extract cyclicity in the DBSM in its particular industrial environment. The system dynamic design has competitive forecasting accuracy relative to univariate time series models and artificial neural networks (ANNs) in terms of forecasting outcomes.

Findings – The results show that the system dynamic design has a better forecasting performance according to three evaluation metrics, mean absolute scale error (MASE), root mean square error (RMSE) and mean absolute percentage error (MAPE).

Originality/value – Cyclical analysis is a significantly useful instrument for shipping asset management, particularly in market entry–exit operations. This paper investigated the cyclical nature of the dry bulk shipping business and estimated significant business cycle periodicity at around 4.5-year frequency (i.e. the Kitchin cycle).

Keywords System dynamics, Business cycle theory, Investment timing, Dry bulk shipping

Paper type Research paper

1. Introduction

Shipping firms deal with two major decision-making processes: (1) long-term asset management led by asset prices (i.e. ship prices) and asset play opportunities (countercyclical investment) and (2) short-term liquidity management led by particular working capital management. Although there are a number of financial management standards for liquidity management, shipping asset management is quite complex and fundamentally depends on shipping markets and predictive analytics. One essential need for shipping asset management is an accurate cyclical projection to develop strategies for investment timing.

Angelopoulos *et al.* (2016) presented one of the first applications of spectral analysis to the long-term dry cargo freight index (Duru and Yoshida, 2011) and extracted cycles in various



frequencies (short- to long-term cycles). The conventional spectral analysis utilizes time-frequency analysis (frequency domain transformation) and estimates significant cyclical frequencies for further assessment. However, the traditional approach investigates the spectral components by using univariate analysis, excluding causal relationships with other drivers of an economic phenomenon (e.g. supply and demand drivers in the shipping markets). System dynamics is a methodology to represent an economic market through causal relationship functions among components of the network, particularly in nonlinear systems. Since economic phenomena include many nonlinear relationships, it is quite difficult to solve problems using standard model equations estimated independently or in a serial design (e.g. simultaneous equations modeling). Forrester (1958) first created the concepts of system dynamics, which is a technique to estimate the nonlinear behavior patterns of a sophisticated system over time using various functions and interactions, such as stocks, flows, internal feedback loops and time delays, among others. There are few applications of system dynamics in shipping economics (Randers and Göluke, 2007; Dikos *et al.*, 2006). In addition to market modeling, system dynamics can also be estimated to extract the consistent cyclical nature of the response variable. In contrast to spectral analysis, system dynamics investigates market cycles in their broader circumstances and only extracts the most significant cycle in any given data frequency. While spectral analysis generates all weak-strong cyclical patterns, system dynamics focuses on a single significant cyclical pattern.

The purpose of this study is twofold. First, this study aims to analyze cycles of dry bulk shipping market (DBSM) Baltic Dry Index (BDI) and time charter rate of Handysize, Panamax, Capesize and Supramax. Second, this study develops a formula for analyzing the cycle and event of the DBSM using system dynamics and compares it with other forecasting models, including autoregressive integrated moving average (ARIMA), regression with autoregressive moving average (regARMA), trigonometric exponential smoothing state-space model with Box–Cox transformation, ARMA errors, trend and seasonal components (TBATS), Holt–Winters (H-W) and artificial neural network model (ANN). This is to confirm the accuracy of the cycle formula developed using system dynamics. If the method we have developed is accurate, the prediction of the DBSM will become easier in the future.

2. Literature reviews

To analyze of the characteristics of volatility in the DBSM, chartering activity has been considered an important evaluation factor to understand the uncertainty of the DBSM, which has been affected by long cycles of the world economy. It is well known that the bulk shipping industry has run into some unexpected cyclic patterns, which include four stages. These stages are expansion, where the business cycle moves above, prosperity, where the business cycle achieves its maximum limit, contraction, where there is a rapid decline in this phase, and recession, where the decline in the business cycle becomes rapid and steady. Although shipping cycles are well known, averaging eight years according to Stopford (2008), estimating cyclical turning points is a difficult issue. There are many academic papers on the bulk shipping market that have analyzed various aspects of shipping market behaviors. This is because both the magnitude and the length of each cycle vary from phase to phase. This makes us examine each cycle as a distinct event. Therefore, high-quality forecasts, including accurate estimations of the cycle patterns, are becoming highly significant for shipping industry stakeholders to make successful investment and charter determinations. If shipping companies are unable to fully understand the cyclical nature of the shipping industry, avoid bad debts and maintain cash flow, they will face some consequences. However, many shipping companies might not be willing to take a risk of bankruptcy, such as Hanjin Shipping and Transfield Shipping, or even declare bankruptcy, for example, Armada Singapore, in the 2008 financial crisis, which was the worst economic crisis since the Great Depression of 1929.

Cyclical analysis and forecasting of the dry bulk market have attracted a great deal of attention from both academics and practitioners. Not surprisingly, then, economists have expended considerable effort on analyzing bulk dry market cycles. Nonetheless, there is a limited amount of literature dealing with the determination of cycle patterns in the DBSM to improve forecast accuracy. The various models to capture cycle pattern and forecast BDI used in the literature are summed up below.

Hampton (1990) held to the idea of a substantial change in the economy after 1990, based on the implementation of the Kondratieff cycle, which is the long-cycle theory of the world economy in the shipping industry. Dikos *et al.* (2006) argued the key factors that affect the tanker rate by using system dynamics modeling and investigated the causal directions. Duru (2010) presented a fuzzy integrated logical forecasting model that improved the latest values and error patterns for dry bulk shipping index prediction. Duru and Yoshida (2011) showed that the log-linear model is not useful because it leads to spurious regression in shipping market forecasting. Duru *et al.* (2012) presented fuzzy extended Delphi with statistical time series adjustment for DBSM prediction. Papailias *et al.* (2017) presented an integrative framework for identifying cyclical patterns, as well as BDI forecasting. They found that it fails to provide accurate forecasts. If the price series is linear, the models in question can generate useful results in terms of forecasting. However, forecasting becomes a challenging task because of nonlinearity in the bulk shipping price series. Artificial intelligence models, neural networks (ANN) and support vector machines (SVMs) have been widely applied successfully in the bulk shipping market. Lyridis *et al.* (2004) focused on nonlinear analysis and used the ANN to forecast the spot rates of very large crude carriers (VLCCs). They put forward a framework for improving forecasting accuracy that considers the past value of freight rates in forecasting. Zeng *et al.* (2016) contributed to improving forecast accuracy by using empirical mode decomposition (EMD). They decomposed the BDI into intrinsic mode functions. In this context, each component was modeled by using ANN. It is concluded that the proposed methodology, a combined EMD-ANN approach, leads to improved forecasting performance rather than the VAR model (based on out-sample results). This paper investigates the cyclicity of DBSM while utilizing causal variables, such as ship fleet or seaborne trade volume. In contrast to Angelopoulos *et al.* (2016), this study does not deal with cyclicity over 15 years (e.g. Kuznet cycles). Angelopoulos *et al.* (2016) indicated that the Kitchin type business cycles (4–5 years) had disappeared or contracted to three-year cycles by 2006. This paper will also investigate the progress of the Kitchin type cycles after the 2008 financial crisis. Finally, the estimated cyclical model will be validated with the out of sample predictive accuracy.

3. Methodologies

This study aimed to compare the out-of-sample forecasting performances of univariate linear time series models, ANN model and system dynamics model by using monthly datasets, such as the BDI index and time charter rates (Handysize, Panamax, Capesize and Supramax). The idea behind these comparisons is to reveal whether the system dynamic, which applies the formula for the cycle of dry bulk shipping, has a better forecasting performance than the linear models and the ANN model. To this end, the seasonal ARIMA (sARIMA) by Box *et al.* (2015), regression with ARMA errors (regARMA), exponential smoothing state-space model with Box Cox transformation, ARMA errors, TBATS and H-W by Winters (1960) models thought to be relevant in considering linear time series models are utilized, and further to this end, a nonlinear model which is an ANN model that can capture and represent input/output relationships is used to forecast the datasets. Multi-layer perceptrons (MLPs) are the most commonly used ANNs in the forecast field (Kaboudan, 2001; Rasouli *et al.*, 2016). In the context of hidden layers in the ANN model, two hidden layers were used in networks with

better performance than networks with one hidden layer (for further details refer to the study by [Thomas et al. \(2017\)](#)).

System dynamics was developed by [Forrester \(1958\)](#). The significant feature of system dynamics is solving nonlinear social problems using causal loop diagrams (CLDs) and stock flow diagrams (SFDs). In system dynamics, problems are expressed through CLD ([Sterman, 2000](#)). The CLD helps to understand the simulation model by simply expressing the causal relationship of the problem (see [Figure 1](#)).

CLDs visualize the simulation conceptual framework and are used for qualitative analysis. Storage and flow diagrams are used for empirical analysis. In system dynamics, the stock is a variable that accumulates or depletes over time. Flow defines the rate of change of the stock. A flow defines the rate of change in stock. The basic formula of stock and flow diagrams is shown in [equation \(1\)](#):

$$\text{Stock}(t) = \text{Stock}(t_0) + \int_{t_0}^{t_n} [\text{inflow}(t) - \text{outflow}(t)] dt \quad (1)$$

4. Empirical study

4.1 Data selection

For the simulation model for spectral analysis of DBSM, we use the following data: (1) the BDI and time charter rate of Handysize, Panamax, Capesize and Supramax, (2) dry bulk trade volume as a demand indicator and (3) total bulk ship fleet as a supply indicator.

The following variables were used by previous research on forecasting of shipping freight rates. [Veenstra and Franses and \(1997\)](#) predicted the BDI using Capesize and Panamax ship of supply and iron ore, coal and grain of demand. [Engelen et al. \(2006\)](#) said that dry bulk market freight rates are formed by demand (traffic volume) and supply (ship capacity), and [Randers and Göluke \(2007\)](#) predicted the oil tanker market using demand (crude oil transport volume) and supply (ship capacity). [Drobetz et al. \(2012\)](#) predicted dry bulk and tanker freight markets using world economy, seaborne commodity trades, the average distance to transport, random shocks and transportation costs for demand, and global fleet, fleet efficiency, shipbuilding production, scrapping and losses and freight earnings for supply. [Jeon and Yeo \(2017\)](#) predicted CCFI (China Containerized Freight Index) using the China seaborne container trade volume for demand and containership 3,000–5,999 twenty-foot equivalent unit (TEU) fleet, 6,000–7,999 TEU fleet, 8,000–11,999 TEU fleet, 12,000–14,999 TEU fleet and 15,000+ TEU fleet ([Iris et al., 2018](#)) for supply. In previous research, shipping freight rates were predicted using many variables, such as classification of ship size, classification of freight volume and economy variables. However, the variables commonly used for forecasting are the trade volume as demand and ship capacity as supply ([Veenstra](#)

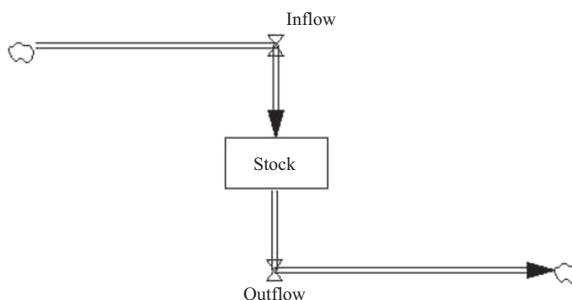


Figure 1.
Fundamental model of
the SFD

and Franses, 1997; Engelen *et al.*, 2006; Randers and Gölüke, 2007; Drobetz *et al.*, 2012). Therefore, this study tried to avoid the multicollinearity problem by simulating the DBSM using the most used variables, demand and supply.

In this study, we used total bulk carrier fleet development as the supply, and the demand variable is the sum of grain exports (Argentina, Australia, Canada, EU28, and USA), iron ore exports (Australia, Brazil) and coal imports (EU-25, South Korea). Region selections were based on the data criteria provided by [Clarkson Shipping Intelligence Network](#). Data (monthly rates) are collected from the *Clarkson Shipping Intelligence Network* from January 2000 to December 2016. [Table 1](#) is a descriptive summary of the data used in the DBSM prediction.

4.2 Causal loop diagram

The CLD used the feedback loop to conceptualize and explain the simulation model. This can be used to explain the simulation model with the causal loop diagram ([Richardson, 1995](#); [Sterman, 2000](#)).

We use dry bulk trade volume of demand indicator, total bulk ship fleet of supply indicator to predict the DBSM indicator (BDI, one-year time charter rate (\$/Day) of Handysize, Panamax, Capesize and Supramax). The BDI is a composite freight index for dry bulk shipping published by the London-based Baltic Exchange. The BDI is classified into Baltic Capesize Index (BCI), Baltic Panamax Index (BPI), Baltic Supramax Index (BSI) and Baltic Hyndy Index (BHSI) according to the size of the vessel. Therefore, in this study, BDI, a composite freight index, was selected as the DBSM indicator. Since the time charter rate includes the market expectations of shipowners or charterers, it was included in the analysis target of this study. However, unlike the BDI, the time charter rate does not have a composite index and is divided into Handysize, Handymax, Panamax and Capesize. Therefore, in this study, the cycle of time charter rate of each ship size is analyzed.

As mentioned above (4.1 Data selection), the dry bulk trade volume is the sum of grain, iron ore and steam coal, and the total bulk ship fleet is the sum of Handysize, Handymax, Panamax, Capesize and Supramax. [Figure 2](#) shows the CLD between the index of DBSM indicator, dry bulk trade volume, total bulk ship fleet and supply and demand balance. Ship oversupply in the shipping market is a big problem. We considered the supply and demand balance to account for this problem. The dry bulk trade volume is chosen to positively impact on the index of the DBSM. In contrast, the total bulk ship fleet and supply and demand balance are chosen to have a negative impact on the index of the DBSM. According to [Luo *et al.* \(2009\)](#) and [Jeon *et al.* \(2020\)](#), ship supply is a major supply indicator for shipping freight rates, and trade volume is a major demand indicator for shipping freight rates. System dynamics constitutes the feedback structure of each variable over time as mentioned above. To simulate changes in DBSM indicator according to changes in the supply and demand indicators over time, the demand and supply indicators are directly linked to the DBSM

Variables (Unit)	Mean	Median	Maximum	Minimum	S.D
BDI (Index)	2524.500	1677.112	10843.650	306.905	2177.219
Capesize (\$/Day)	35889.860	21546.880	161600.000	6131.250	35173.080
Demand (Thousand tonnes)	90574.580	86118.110	148000.900	43277.440	27555.630
Handysize (\$/Day)	12478.980	9392.453	39719.160	4652.863	7850.681
Panamax (\$/Day)	20063.030	13250.000	79375.000	5362.500	16724.860
Supply (Million DWT)	473.052	401.588	788.921	267.209	181.964
Supramax (\$/Day)	17794.160	12387.500	66300.000	4875.000	13550.960

Table 1.
Descriptive statistics of
the sample data

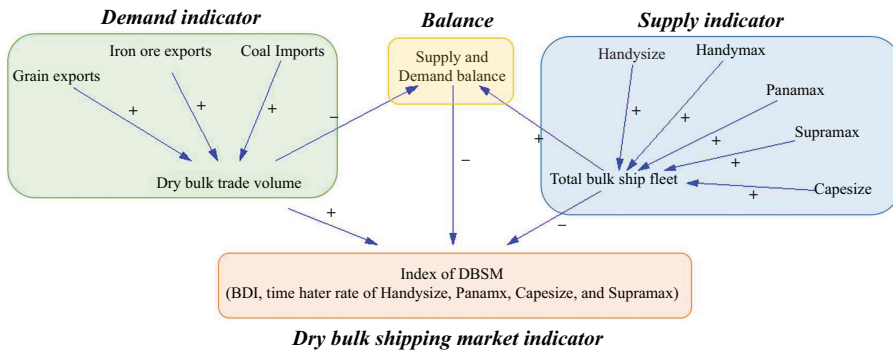


Figure 2. Causal loop diagram

indicator. In this study, we first simulate the dry bulk trade volume and total bulk ship fleet and then normalize each sub-model to predict the index of the DBSM.

4.3 Stock flow diagram

The SFD has been visualized in Figure 3 to analyze the cycle in the dry bulk shipping market. The SFD for analyzing the cycle in the DBSM consists of three sub-models: dry bulk trade volume, total bulk ship fleet and supply and demand balance. The SFD based on the relationship between variables is illustrated in Section 4.2.

The initial value of the SFD is from January 2000, and the time step is one month. The precision of the SFD was corroborated by examining the difference between the postsample data (2017) and the data from 2000 to 2016. The SFD has been developed by using Vensim computing platform.

The multicollinearity is a problem in which strong correlations between independent variables appear. We performed correlation analysis to determine the correlation between each variable. As a result of the correlation analysis of trade volume, the correlation between iron ore and coal was 0.862 and that of iron ore and grain was 0.795. In addition, a correlation analysis of supply was performed. As a result of correlation analysis, Panamax and Capesize were 0.994, Capesize and Supramax were 0.923 and Handymax and Panamax were 0.996, indicating a high correlation. If a highly correlated variable is used as each variable, the

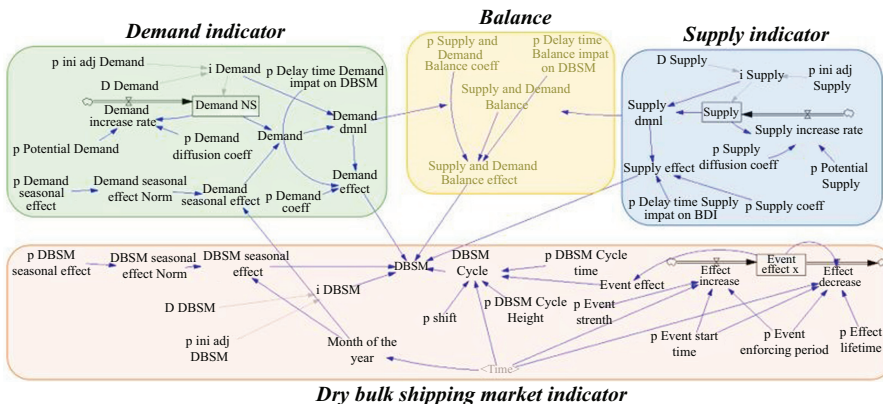


Figure 3. Stock-flow diagram

coefficient of influence on the BDI is not calculated properly, so we used demand and supply as the sum of each.

Iron ore, coal and grain trades generate majority of dry bulk shipping flow. We used the sum of grain, iron ore and coal trade volume (tonnes of cargo) as an indicator of demand to avoid multi-collinearity problems. It is simulated using [equation \(2\)–\(3\)](#).

The total fleet size of Handysize, Handymax, Panamax, Capesize and Supramax tonnages are utilized as the supply indicators in the DBSM. Small bulk ships (Handysize, Handymax) have little to do with transporting iron ore and coal. However, small bulk ships (Handysize, Handymax) are involved in the transport of grain. In the data provided by the [Clarkson Shipping Intelligence Network](#), there is no trade volume by ship size, so the sum of ship size is used as a supply indicator. The supply indicators are also converted to the total fleet to avoid the multi-collinearity problem. If Handysize, Handymax, Panamax, Capesize and Supramax are simulated to affect the BDI for each of the ship supply variables, the supply effect coefficient is not calculated properly due to the multicollinearity problem. Therefore, we used the sum of Handysize, Handymax, Panamax, Capesize and Supramax as a supply index. They are simulated using [equation \(4\)–\(5\)](#). As the supply indicator increases, the shipping freight rate decreases, and when the demand increases, the shipping freight rate increases, so the balance variable was simulated to have a negative effect. The supply and demand indicators are normalized before conducting the simulation, and the supply–demand interaction component is estimated by using the Supply-Demand Balance function ([equation 6](#)).

We simulated indicators of the DBSM to have a positive impact on demand and the supply and demand balance to have a negative impact on the indicators of the DBSM. In order to standardize the demand and supply, both datasets are normalized to their initial values. The time at which the above variables affect indicators of the DBSM is different. The time lag has been calculated by a delay function (DELAY1 (in, DTIME)). The level of the impact and time delay of the standardized variables to the indicator of DBSM is calculated using the calibration function. The equations for simulating BDI are (7)–(14). We apply [equation \(11\)](#) to analyze the cycle of indicator of DBSM and [equation \(12\)–\(14\)](#) to analyze events affecting the cycle of indicator of DBSM.

$$\text{Demand} = i\text{Demand}_{ns}(t_0) * i\text{Demand}_p + \int_{t_0}^{t_n} [\text{Demand increase}(t)] dt * s\text{Demand}_p \quad (2)$$

$$\text{Demand increase}(t) = (p\text{Demand}_p - \text{Demand}(t)) * \text{Demand}(t) / p\text{Demand}_p * d\text{Demand}_p \quad (3)$$

$$\text{Supply} = i\text{Supply}(t_0) * i\text{Supply}_p + \int_{t_0}^{t_n} [\text{Supply increase}(t)] dt \quad (4)$$

$$\text{Supply increase}(t) = (p\text{Supply}_p - \text{Supply}(t)) * \text{Supply}(t) / p\text{Supply}_p * d\text{Supply}_p \quad (5)$$

$$\text{Supply and demand balance} = \text{abs} \left(\left(\frac{\text{Supply}}{i\text{Supply} * i\text{Supply}_p} \right) - \left(\frac{\text{Demand}}{i\text{Demand} * i\text{Demand}_p} \right) \right) \quad (6)$$

$$\text{DBSM} = i\text{DBSM} * i\text{DBSM}_p * s\text{DBSM}_p * \text{Demand effect} * \text{Supply effect} * \text{Supply and demand balance effect} * \text{DBSM cycle} \quad (7)$$

Demand effect

$$= \text{DELAY1} \left(\left(\frac{\text{Demand}}{i\text{Demand} * i\text{Demand}_p} \right)^{e\text{Demand}_p}, \text{Delay time Demand impact on DBSM}_p \right) \quad (8)$$

Supply effect

$$= \text{DELAY1} \left(\left(\frac{1}{\left(\frac{\text{Supply}}{i\text{Supply} * i\text{Supply}_p} \right)^{e\text{Supply}_p}} \right), \text{Delay time Supply impact on DBSM}_p \right) \quad (9)$$

Supply and demand balance effect

$$= \text{DELAY1} \left(\frac{1}{\left(\frac{\text{Supply and demand balance}}{i\text{Supply and demand balance}_p} \right)^{e\text{Supply and demand balance}_p}}, \text{Delay time Balance impact on DBSM}_p \right) \quad (10)$$

$$\text{DBSM cycle} = 1 + \text{DBSM}_p * \text{SIN}(2 * 3.14159) * \frac{\text{Time} - \text{shift}_p}{\text{CCT}_p} * \text{Event effect}(t) \quad (11)$$

$$\text{Event effect}(t) = 0(t_0) + \int_{t_0}^{t_n} [\text{Effect increase}(t) - \text{Effect decrease}(t)] dt \quad (12)$$

$$\begin{aligned} \text{Effect increase}(t) &= \text{IF THEN ELSE}(\text{Time} > \text{EST}_p : \text{AND} : \text{Time} < \\ &= \text{EST}_p + \text{EEP}_p, \text{ES}_p / \text{EEP}_p, 0) \end{aligned} \quad (13)$$

$$\text{Effect decrease}(t) = \text{IF THEN ELSE}(\text{Time} > \text{EST}_p + \text{EEP}_p, \text{Event Effect}(t) / \text{ELT}_p, 0) \quad (14)$$

Note that (t) represents the time step, while (t_0) is the initial time in the SFD. dt refers to the time duration of the simulation. $i\text{Demand}_p$, $i\text{Supply}_p$ and $i\text{DBSM}_p$ are an initial adjustment parameter. $s\text{Demand}_p$ and $s\text{DBSM}_p$ are a seasonality parameter, and $p\text{Demand}_p$ and $p\text{Supply}_p$ are potential growth parameter. $d\text{Demand}_p$ and $d\text{Supply}_p$ are diffusion parameters. $e\text{Demand}_p$, $e\text{Supply}_p$ and $e\text{Supply and demand balance}_p$ are the effect degree parameter on the DBSM. Delay time Demand impact on DBSM_p, Delay time Supply impact on DBSM_p and Delay time Balance impact on DBSM_p are the time lag parameters. To analyze the DBSM's cycle, we utilized the simulation model presented by Jeon *et al.* (2020). The variables used in Figure 3 are expressed as abbreviations in the formula below. Abbreviations and definitions used in the formula are shown in Table 2. The optimal values for all parameters used in the simulation model were derived by using Vensim's calibration function, shown in Table 3.

4.4 Model validation

The mean absolute scaled error (MASE) is used to check predictive accuracy of the SFD and benchmarks (ARIMA, regARMA, TBATS, H-W Model and ANN). The MASE is a method that can be used for general forecast validity by Hyndman and Koehler (2006). The following equation is estimated for MASE:

Table 2.
Nomenclature

Abbreviations used in formulas	Definition	Variable names used in Figure 3
$iDemand_p$	Parameter for initial value adjustment of demand	p ini adj Demand
$iSupply_p$	Parameter for initial value adjustment of supply	p ini adj supply
$iDBSM_p$	Parameter for initial value adjustment of DBSM	p ini adj BDI
$dDemand_p$	Diffusion parameter of demand	p Demand diffusion coeff
$dSupply_p$	Diffusion parameter of supply	p supply diffusion coeff
$\rho Demand_p$	Parameter for potential growth of Demand	p Potential Demand
$\rho Supply_p$	Parameter for potential growth of supply	p Potential supply
$sDemand_p$	Seasonality parameter of supply	p Demand seasonal effect
$sDBSM_p$	Seasonality parameter of DBSM	p BDI seasonal effect
$eDemand_p$	Effect parameter of demand	p Demand coeff
$eSupply_p$	Effect parameter of supply	p supply coeff
$eSupply\ and\ demand\ balance_p$	Effect parameter of balance	p supply and Demand balance coeff
Delay time Demand impact on DBSM $_p$	Delay time Demand impact on DBSM	p Delay time Demand impact on DBSM
Delay time Supply impact on DBSM $_p$	Delay time supply impact on DBSM	p Delay time supply impact on DBSM
Delay time Balance impact on DBSM $_p$	Delay time balance impact on DBSM	p Delay time balance impact on DBSM
DBSMH $_p$	Parameter for DBSM cycle height	p BDI cycle height
DBSMT $_p$	Parameter for DBSM cycle time	p BDI cycle time
shift $_p$	Parameter for start time of DBSM cycle	p Shift
EST $_p$	Event start time	p Event start time
EEP $_p$	Event enforcing period	p Event enforcing period
ES $_p$	Event strength	p Event strength
EELT $_p$	Lifetime of event effect	p Effect lifetime

$$MASE = \text{mean}(|q_t|) \tag{15}$$

$$q_t = \frac{e_t}{\frac{1}{n-1} \sum_{i=2}^n |y_i - y_{i-1}|} \tag{16}$$

where e_t represents the prediction error and $y_i - y_{i-1}$ is the prediction error of the naive forecast. Postsample data of 2017 was used to examine the precision of the DBSM's simulation results.

To verify the accuracy of indicator of DBSM, the simulation results of the indicator of DBSM is compared with the postsample data (2017). In Figure 4, line 1 is the actual data, line 2 is the simulation result and line 3 is the postsample data. Tables 4 and 5 display the precise outcomes of the simulation model. We compared the indicator of DBSM simulation results with ARIMA, regARMA, TBATS, H-W Model, ANN and system dynamics methods. Simulation results using system dynamics among the three models were found to be most

Parameter	Values (Units)
$iDemand_p$	0.716696 (dmnl)
$pDemand_p$	180,865 (Thousand tonnes)
$dDemand_p$	0.012 (1/month)
$sDemand_p$	JAN = 1.000, FEB = 0.943, MAR = 1.044 APR = 1.026, MAY = 1.026, JUN = 0.993 JUL = 1.051, AUG = 1.039, SEPT = 1.058 OCT = 1.024, NOV = 1.012, DEC = 1.063 (dmnl)
$iSupply_p$	0.739 (dmnl)
$pSupply_p$	1815.08 (million DWT)
$dSupply_p$	0.009 (1/month)
$iDBSM_p$	1.12163 (dmnl)
$sDBSM_p$	JAN = 1.000, FEB = 0.979, MAR = 1.132 APR = 1.107, MAY = 1.249, JUN = 1.1480 JUL = 1.087, AUG = 0.968, SEPT = 1.141 OCT = 1.301, NOV = 1.332, DEC = 1.279 (dmnl)
$eDemand_p$	1.54164 (dmnl)
$eSupply_p$	1.50431 (dmnl)
$eSupply$ and demand balance $_p$	1.206 (dmnl)
Delay time Demand impact on DBSM $_p$	1.082 (month)
Delay time Supply impact on DBSM $_p$	2.756 (month)
Delay time Balance impact on DBSM $_p$	0.864 (month)
shift $_p$	29.960 (dmnl)
DCH $_p$	0.419 (dmnl)
DCT $_p$	52.985 (month)
EST $_p$	41, 102, 127 (month)
EEP $_p$	8, 2, 4 (month)
ES $_p$	1.254, -0.952, -0.343 (dmnl)
EELT $_p$	2, 24, 499 (month)

Table 3.
Parameters of the
simulation model
(based on BDI)

accurate in the postsample period except for Supramax. System dynamics ranked second in Supramax predictions in the postsample period.

4.5 Cycle analysis

The aim of this paper is to research the cyclical nature of the DBSM so that dry bulk shipping decision-makers can develop projections and respond to market changes. We use [equation \(11\)–\(14\)](#) to analyze the DBSM cycle and discover events that affect the cycle. The results of the DBSM cycle are shown in [Figure 5](#).

The system dynamics approach found a significant Kitchin type business cycle at 53–56 months (BDI: 53 months, Handysize: 56 months, Panamax: 55 months, Capesize: 55 months and Supramax: 55 months) frequency similar to the findings of previous studies ([Rander and Gölüke, 2007](#); [Goulielmos and Psifia, 2011](#)).

We found three events that affected the DBSM cycle from 2000 to 2016. First, in June 2003, the indicator of the DBSM rose massively. In 2003, the indicator of the DBSM increased sharply due to a surge in raw material demand. This was due to the dramatic rise of the Chinese economy, which was led by high volume of production and trade. Second, in July 2008, the indicator of the DBSM decreased sharply due to the global financial crisis, which caused a sudden shortage in trade volume. Third, in August 2010, the indicator of the DBSM decreased due to intensive dry bulk ship orders between 2006 and 2007, which were scheduled to be delivered in the 2009–2010 period, which caused an oversupply during that period and the following years.

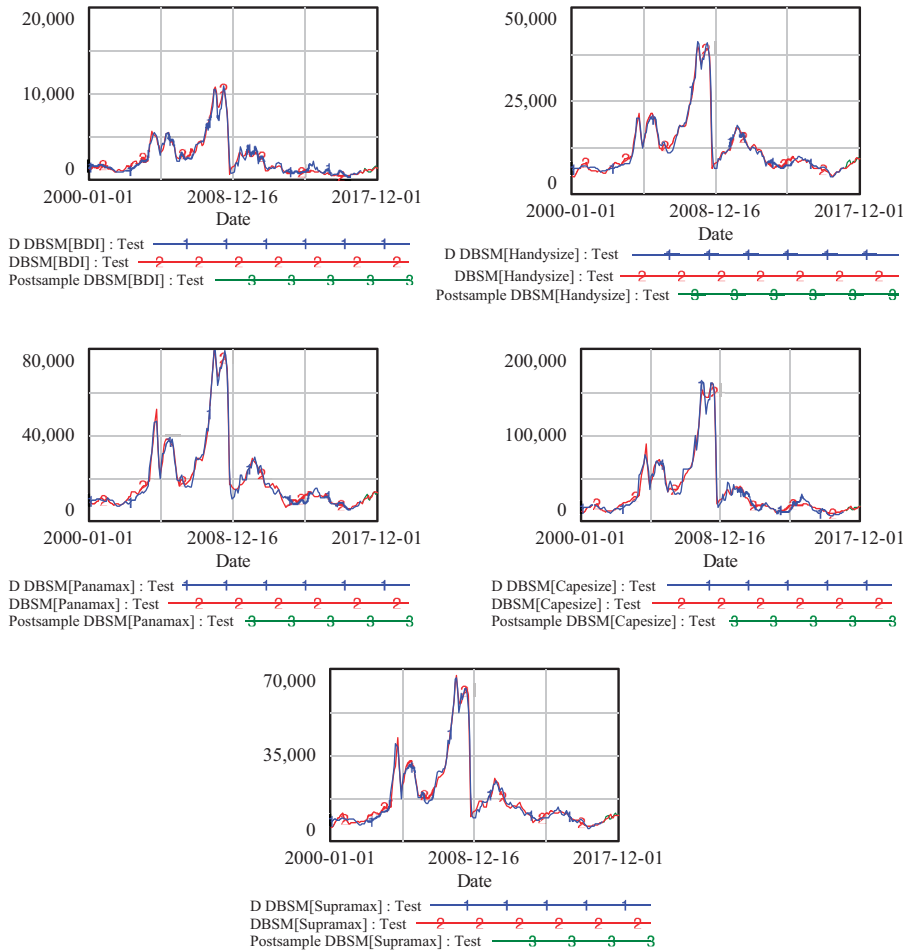


Figure 4.
BDI system dynamics
simulation result

5. Discussion

The system dynamics approach found a significant Kitchin type business cycle at 53–56 months (BDI: 53 months, Handysize: 56 months, Panamax: 55 months, Capesize: 55 months and Supramax: 55 months) frequency similar to the findings of [Rander and Göluke \(2007\)](#) or [Goulielmos and Psifa \(2011\)](#). In [Randers and Göluke \(2007\)](#), the tanker freight rates cycle is found at four years. Compared with the previous study, our result of the DBSM cycle identifies a similar cyclical pattern. Bulk shipping market requires a large initial investment for ship investment, but it is easy to raise funds with the development of the ship finance. In addition, unlike the liner's shipping market, it can operate a business with a small fleet, so entry barriers are low. As a result, more than 1,500 shipping companies are competing worldwide, and the top shipping companies in terms of transportation capacity have only a 3% share. In addition, the fundamental differences in the services provided by shipping companies are not great. Bulk transportation requires a large initial investment in ship investment, but it is easy to raise funds with the development of ship finance. In addition, unlike the container market, it can operate a business with a small fleet, so entry barriers are

Models	Training/Estimation (Sample period)		Test (Out of sample period)	
	Period	MASE	Period	MASE
<i>BDI</i>				
ARIMA(0,1,1)	2000–2016	0.147	2017	0.116
Reg with ARMA	2000–2016	0.149	2017	0.122
TBATS	2000–2016	0.142	2017	0.110
HW additive	2000–2016	0.161	2017	0.109
HW multiplicative	2000–2016	0.150	2017	0.074
ANN(lag 2, $c(10,11)$)	2000–2016	0.182	2017	0.076
System dynamics	2000–2016	<i>0.138*</i>	2017	<i>0.067*</i>
<i>Handysize</i>				
ARIMA(1,1,4) (1,0,0)[12]	2000–2016	0.096	2017	0.141
Reg with ARMA	2000–2016	0.094	2017	0.094
TBATS	2000–2016	<i>0.091*</i>	2017	1.000
HW additive	2000–2016	0.103	2017	0.086
HW multiplicative	2000–2016	0.105	2017	0.160
ANN(lag 2, $c(9,9)$)	2000–2016	0.096	2017	0.053
System dynamics	2000–2016	0.098	2017	<i>0.047*</i>
<i>Panamax</i>				
ARIMA(2,1,1) (0,0,1)[12]	2000–2016	0.101	2017	0.183
Reg with ARMA	2000–2016	0.101	2017	0.174
TBATS	2000–2016	1.00	2017	0.161
HW additive	2000–2016	0.114	2017	0.068
HW multiplicative	2000–2016	0.112	2017	0.042
ANN(lag 2, $c(9,9)$)	2000–2016	0.100	2017	0.064
System dynamics	2000–2016	<i>0.096*</i>	2017	<i>0.036*</i>
<i>Capesize</i>				
ARIMA(2,1,1) (0,0,1)[12]	2000–2016	0.117	2017	0.151
Reg with ARMA	2000–2016	0.118	2017	0.110
TBATS	2000–2016	0.116	2017	0.140
HW additive	2000–2016	0.127	2017	0.098
HW multiplicative	2000–2016	0.119	2017	0.122
ANN(lag 2, $c(9,9)$)	2000–2016	0.125	2017	0.036
System dynamics	2000–2016	<i>0.113*</i>	2017	<i>0.034*</i>
<i>Supramax</i>				
ARIMA(2,1,1) (0,0,1)[12]	2000–2016	0.099	2017	0.125
Reg with ARMA	2000–2016	0.099	2017	0.094
TBATS	2000–2016	<i>0.096*</i>	2017	0.083
HW additive	2000–2016	0.110	2017	0.059
HW multiplicative	2000–2016	0.103	2017	0.066
ANN(lag 2, $c(9,9)$)	2000–2016	0.097	2017	<i>0.050*</i>
System dynamics	2000–2016	0.100	2017	0.053

Note(s): *Italic figures indicate the minimum error rate in given column

Table 4.
MASE predictive accuracy of cyclical model comparing to ARIMA, regARIMA, TBATS, H-W Model and ANN methods

low. Due to these characteristics, the bulk market shipping market is close to perfect competition, and the change rate of freight rates according to external factors (world economy, supply, demand conditions, etc.) is rapidly appearing. In this study, the cycle of the DBSM was analyzed similarly to the previous study. This is because the data collection period for this study started in 2000. This study is significant in analyzing the events that affect the cycle of the DBSM since 2000. In future research, it is necessary to identify the

Models	Period	Test (Out of sample period)		MAPE
		MASE	RMSE	
<i>BDI</i>				
ARIMA(0,1,1)	2017	0.116	0.299	0.151
Reg with ARMA	2017	0.122	0.338	0.152
TBATS	2017	0.110	0.310	0.179
HW additive	2017	0.109	0.263	0.197
HW multiplicative	2017	0.074	<i>0.182*</i>	0.135
ANN(lag 2, c(10,11))	2017	0.076	0.195	0.153
System dynamics	2017	<i>0.067*</i>	0.185	<i>0.133*</i>
<i>Handysize</i>				
ARIMA(1,1,4) (1,0,0)[12]	2017	0.141	0.127	0.125
Reg with ARMA	2017	0.094	0.094	0.083
TBATS	2017	1.000	0.087	0.089
HW additive	2017	0.086	0.092	0.074
HW multiplicative	2017	0.160	0.143	0.107
ANN(lag 2, c(9,9))	2017	0.053	0.059	0.048
System dynamics	2017	<i>0.047*</i>	<i>0.055*</i>	<i>0.043*</i>
<i>Panamax</i>				
ARIMA(2,1,1) (0,0,1)[12]	2017	0.183	0.344	0.251
Reg with ARMA	2017	0.174	0.332	0.239
TBATS	2017	0.161	0.308	0.220
HW additive	2017	0.068	0.142	0.093
HW multiplicative	2017	0.042	0.081	0.060
ANN(lag 2, c(9,9))	2017	0.064	0.126	0.094
System dynamics	2017	<i>0.036*</i>	<i>0.078*</i>	<i>0.054*</i>
<i>Capesize</i>				
ARIMA(2,1,1) (0,0,1)[12]	2017	0.151	0.564	0.339
Reg with ARMA	2017	0.110	0.431	0.245
TBATS	2017	0.140	0.526	0.315
HW additive	2017	0.098	0.378	0.224
HW multiplicative	2017	0.122	0.457	0.275
ANN(lag 2, c(9,9))	2017	0.036	0.151	0.082
System dynamics	2017	<i>0.034*</i>	<i>0.134*</i>	<i>0.082*</i>
<i>Supramax</i>				
ARIMA(2,1,1) (0,0,1)[12]	2017	0.125	0.189	0.165
Reg with ARMA	2017	0.094	0.156	0.123
TBATS	2017	0.083	0.129	0.111
HW additive	2017	0.059	0.104	0.077
HW multiplicative	2017	0.066	0.104	0.087
ANN(lag 2, c(9,9))	2017	<i>0.050*</i>	<i>0.076*</i>	<i>0.069*</i>
System dynamics	2017	0.053	0.093	0.075

Table 5. Comparison of predictive accuracy metrics (MASE, RMASE and MAPE)

Note(s): *Italic figures indicate the minimum error rate in given column

change in the cycle of DBSM by dividing the period, and it is necessary to analyze the cycle after COVID-19.

In this research framework, we aimed to understand the effectiveness of system dynamics modeling in the DBSM to guide shipowners and decision-makers. The more accurate the decisions on the DBSM condition that shipowners make, the more of a competitive advantage they get. The ability to make more accurate decisions is based on knowledge and experience (Scarsi, 2007). The presence of shipowners with knowledge and experience, and the finding of

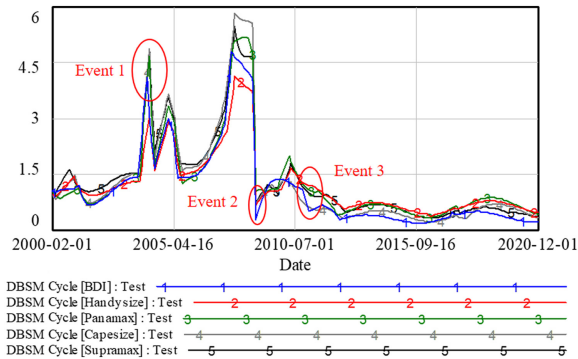


Figure 5.
Cycle analysis result

this study, which confirms the existence of cycles in the DBSM, can help a better understanding of a cycle that can reverse and change vastly on different time scales. Investors have encountered difficulty in understanding the complicated and unstable nature of the shipping industry when it comes to making ship investment decisions (Fan and Luo, 2013). The number of ship orders, whose estimated time of delivery is from two to four years, is based on the DBSM. Oversupply in the DBSM as part of the delivery of ships, particularly during a boom period, can lead to cheaper shipping freight rates. Accordingly, in such situations, proper timing of investment is one of the most important indicators for shipping companies to maintain market competitiveness. Shipping companies can have superiority over others by making a more accurate prediction of shipping cycles; thus, they can attain competitive advantage. The proposed cycle analysis method in the DBSM helps the optimal ship investment timing in terms of shipping companies. In addition, the cycle analysis of the DBSM in this study is useful to decision-makers in determining proper investment timing for the ships in terms of policy planning.

6. Conclusion

Cyclical analysis is a significantly useful instrument for shipping asset management, particularly in market entry–exit operations. This paper investigated the cyclical nature of the dry bulk shipping business and estimated significant business cycle periodicity at around 4.5-year frequency (i.e. the Kitchin cycle). As presented in Figure 5, the recent increase in dry bulk freight rates also validates the significance of a Kitchin type cycle between 2016 and 2021. Based on the empirical results, we expect the increasing trend to be sustained in the following one or two years before shrinking through 2021.

The following are the research findings: First, our research paper provides guidelines for cycles of the DBSM to help the decision-makers, including ship investors, shipbuilders, policymakers and ports. Second, it is possible to make more accurate forecasts by using the cycle formulas presented in this study. In general, shipping markets are difficult to predict due to volatility. Using the cycle formula presented in this study, the system dynamic method is found to be more accurate than other forecasting methods. If the shipping industry decision-makers use our methods to make predictions, they can make more accurate decisions. Additionally, the main finding in this study is that the system dynamics method, which includes other factors as inputs in the model, produces better forecasts than the univariate models and the ANN model because the cyclical patterns may emerge out of other factors, such as economic or noneconomic factors. Specifically, this study aims to guide researchers to bring a new perspective to their methodologies and thus enable them to obtain higher forecasting accuracy by including cyclical patterns in the forecasting process.

This study is meaningful in that it discovered events in the DBSM, but it has the following limitations. First, a simulation model was constructed based on supply and demand indicators. In future research, it is necessary to build a simulation model considering speed of the fleet, utilization rate, port congestion, transport distance, etc. Second, the simulation model of this study did not secure the cargo volume by ship size, so the sum of ship by size and trade volume were used as indicators. In future research, it is necessary to construct a simulation model by classifying the cargo volume by ship size. Third, the data collected through the budget and period secured in this study are from 2000 to 2016. In future research, it is necessary to secure the latest data, and it is necessary to analyze the cycle by period (e.g. 2000–2010, 2010–2020, after COVID-19).

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