An econophysics approach to forecast bulk shipbuilding orderbook: an application of Newton's law of gravitation

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1. Introduction

The new bulk shipbuilding order injects fluidity in the bulk shipping market, provides insight into the global economy, and remains an important indicator to decision making in shipping investments. The research on newbuilding order forecasting in the academic arena is scarce. Commercial newbuilding order forecasts are also either inaccessible and unclear or complex with outcomes that frequently go off beam. The absence of effective but flexible forecasting methodology that could manage the intricacy of the newbuilding domain seems the plausible cause of research scarcity in bulk shipbuilding order forecasting. The earlier research that addresses the bulk shipbuilding order forecasting advocate supply and demand model (Nielsen et al., 1982), ARMA based fleet renewal decision model (Yang et al., 2019), system dynamics model (Wada et al., 2018), time-series analysis (Stopford, 2001, Chen et al., 2014), vessel-based logit model (Alizadeh et al., 2016) and judgmental approach (Duru and Yoshida, 2009, Ariel, 1989). These models reflect on the high volatility of the complex bulk shipbuilding orderbook with a small number of parameters. Consequently, the outcomes of the forecasting models either go astray or remain less explainable. Econophysics approach of modelling can be useful with the flexibility to address this intricacy of the bulk shipbuilding orderbook forecasting.

Econophysics is a hybrid field that houses the strengths of both economics and physics and creates a bridge over a volatile and complex scenario (Chen and Li, 2012, Mantegna, 2016). It is a marriage between social and physical sciences (Schinckus, 2010) that provides a completely new avenue to address multifarious business environments, where careful assumptions of economics and empirical trends of physics resonate together providing meaningful elucidation. Though influenced by diverse constructs and conjectures, shipping is yet to embrace the econophysics approach of inference.

However, there are successful instances of applying econophysics approach in fields that include business volatility and stock markets, economic value and growth, economic and financial time series, behavioural finance, corporation financial stability, distribution and interactions of economic entities, market structure and financial risks (Chen and Li, 2012, Chakraborti et al., 2011, Huang, 2015, Guedes et al., 2019, Schinckus and Jovanovic, 2013, Zapart, 2015, McCauley, 2004, Meng et al., 2016, Rickles, 2007, Zhong et al., 2019). Mainly the concepts of physics such as Bernoulli's equation, Newton's law of gravitation, Brownian motion, Schrodinger equation, Bose-Einstein distribution, Gaussian function, Fourier transformation, and Heisenberg's uncertainty principle have been adopted to naturalise the econophysics models (Donmez and Sen, 2018, Meng et al., 2016, Zhang and Huang, 2010, Cotfas, 2013, Pedram, 2012, Mantegna, 2016, Kusmartsev, 2011, Agustini et al., 2018, Hsu, 2010, Wang and Pei, 2015). This study illustrates a flexible econophysics model that can manage numerous relevant constructs of bulk shipbuilding order forecasting by utilising Newton's law of gravity.

Previously, Newton's law of gravity has been utilised in international trade to model bilateral trading flow and efficiency (Tinbergen, 1962, Abidin et al., 2013, Bialynicka-Birula, 2015), and in the regional study to investigate regional integration effect (Darku, 2009). In this study, Newton's law of gravitation has been naturalised for a bulk shipbuilding order forecasting model by developing predictors or variables with concerned constructs informed through the literature review on trends and factors of shipbuilding. Not all factors have been accommodated into the predictors either because of the relational distance with predictors or due to the non-availability of data. The developed model has been evaluated and trained through the ARIMA analysis technique of the SPSS software.

In the rest of the paper, section 2 presents the literature review and sets the ground for developing predictors. Section 3 elaborates on the econophysics methodology. Section 4 illustrates data analysis and discusses the bulk shipbuilding forecast outcomes of this study. Section 5 is the conclusion.

2. Literature Review

2.1 Trends of shipbuilding industry

Booms and bursts are common in the shipbuilding industry. China, South Korea and Japan are now the leading shipbuilding nations in the world. In each shipbuilding segment, these countries are competing with each other trying to optimise on their shipbuilding capabilities and deliveries. The bulk shipbuilding dominates in the newbuilding orderbook. Bulk shipping mainly serves the global resources sector; as a result, the bulk newbuilding order indicates the global production and economic dynamism. Figures 1 and 2 present segment-wise newbuilding order trends and newbuilding deliveries of the leading shipbuilding nations respectively.

The bulk shipping freight task is a dominating part in the growth of international seaborne freight transportation task (in tonne-km) that indicates the demand-side of shipping capacity (UNCTAD, 2018a). The global economic growth affects trade. Trade derives international seaborne-freight transportation task, where bulk shipping remains critical. However, the evolution of bulk fleet capacity presents the supply-side that is determined by subtracting the demolition figure from the summation of existing fleet and new delivery figures. Therefore, ship demolition and new delivery dynamics become crucial in meeting the seaborne-trade derived freight-transportation demand.

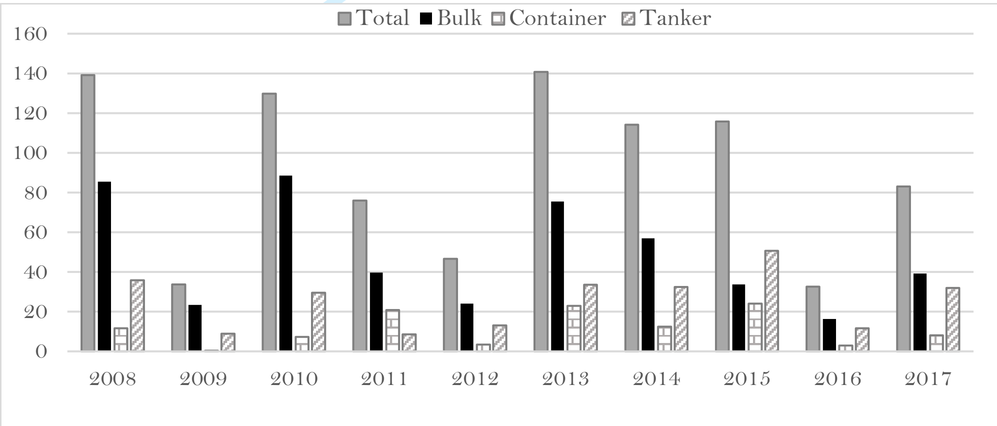


Figure 1: Newbuilding order trends of the main ship segments (in M Dwt)
Data sources: BRS Group (2019), (BRS Group, 2017, BRS Group, 2018)

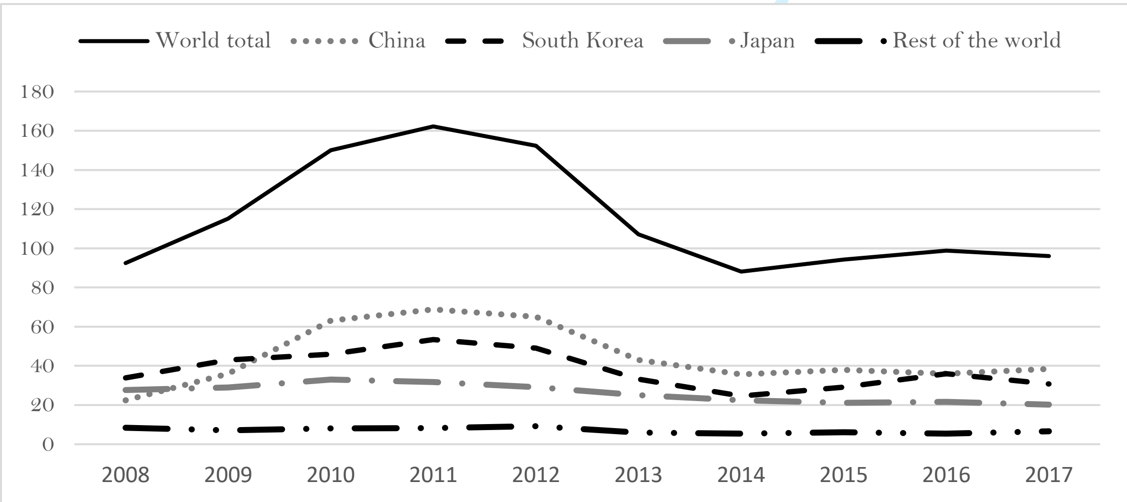


Figure 2: Newbuilding delivery trends of dominating shipbuilding countries (all ship types in M Dwt)
Data sources: BRS Group (2019), (BRS Group, 2017, BRS Group, 2018)

Capacity oversupply also persists in shipping industry. Figure 3 illustrates the global shipbuilding delivery, demolition and seaborne-trade trends. One of the consequences of shipping capacity oversupply is the low shipping freight-rate that mainly fluctuates based on the demand of international seaborne-freight transportation task and the supply of the vessel capacity. Nevertheless, the prospect of favourable future freight-rate drives the newbuilding order (Stopford, 2009).

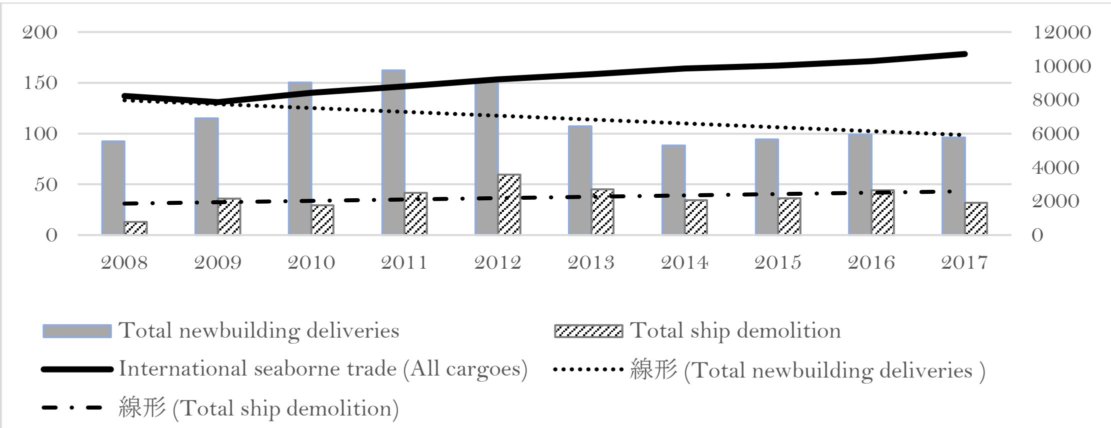


Figure 3: Worldwide shipbuilding delivery, demolition and seaborne trade trends
Data source: BRS Group (2019), (UNCTAD, 2018b)

The growth of shipbuilding is also explainable through newbuilding ship price and scrap price. The newbuilding prices in the dry bulk sector are related to the current and expected freight rates and global economic growth (Beenstock, 1985). Firstly, the growth of world trade and heavy industries boost newbuilding market (Imai, 2008); secondly, the uncertainty in global economic growth and freight-rate volatility affect the shipbuilding market; finally, the adoption of systematised technology and innovation provide leverage to newbuilding (Lim et al., 2017). The factors concerning these drivers require a closer look for shipbuilding order forecasting study.

2.2 Factors impacting shipbuilding

Shipbuilding order forecasting is a complex, cumbersome and less researched area. It is because the growth of the industry is nonlinear and is affected by various volatile and exogenous factors such as international political events and the strategy of shipbuilding nations. The confidential characteristics of the shipbuilding market is another reason for limited research (Charemza and Gronicki, 1981). However, determining an appropriate timing for investment in new shipbuilding is regarded as a mysterious quality (Goulielmos and Psifia, 2009), where forecasting in the short-term can play a critical role.

Historically, international politics and implementation of international regulations affect the shipbuilding industry. In the past, the shipbuilding industry was influenced by political intervention, pre-war demand, post-war redevelopment due to wartime losses, Suez Canal closure, shortage of shipbuilding capacity (dockyard shortage), government credit and incentive schemes, continuous recession (1920-1942 period), and 1980s depressions etc. (Stopford, 2009). The governments' protective views and over-optimism bring in subsidies that also distort the shipbuilding industry, and frequently ship-owners' unconstructive attitudes towards global trade growth cause over-supply that eventually impact shipbuilding industry (Stopford, 1987, Chou and Chang, 2004). In the present time, economic competitiveness, new management system, and innovative technology become critical for newbuilding order attraction (Zheng et al., 2013, Vishnevskiy et al., 2017, Jha, 2016). From ship's operational perspective, the ship speed has an impact on newbuilding; for instance, a slow speed generates more supply requirement for the same quantity of seaborne-freight transportation task and vice-versa. Speed reduction also assists balancing oversupply rather than accelerating newbuilding order. However, the ultimate competition in newbuilding largely depends on the level of demand and supply volatility, shipbuilding price, ship-owners' attitudes towards demand volatility, and shipbuilding nations' strategy (Shin and Lim, 2014).

A consistent shipbuilding decision requires a well-thought forward planning to meet a situation where a continuous demand may exist. Kavussanos and Alizadeh (2002) illustrate that current market rates and long-term equilibrium rates influence newbuilding, particularly in the dry-bulk market. Irrespective of ship-sizes and freight-rate volatility, influential factors for newbuilding order include exchange rate volatility, shipyard capacity change, and shipbuilding cost volatility (Dai et al., 2015). However, the quality data on these factors are either not available or inaccessible. Existing data quality is improving though (Halim et al., 2019). For bulk shipbuilding order forecasting model, it is important to focus on the balancing factors of demand and supply sides of the market that forms the core part of the newbuilding activity (Stopford, 2009). In other words, global economic growth, freight-rate volatility and systematised technology play a crucial role in shipbuilding decisions for ship-owners. Adopting new technology in shipbuilding decision is leveraged through the demolition market. For demolition, the ships of age 20 years and above are always regarded as best candidates (Stopford and Barton, 1986, BRS Group, 2019). The scrap price leverages the newbuilding decision. Hence, the ship demolition market appears as a balancing element between the supply and demand that ultimately drives the market equilibrium and freight-rate level (Karlis and Polemis, 2016). The newbuilding price index affects the shipbuilding orders. The banking system that provides a letter of credit for shipbuilding also focuses on the newbuilding price index. Hence, the ratio of scrap price to newbuilding price index is directly related to the newbuilding order. The higher the ratio the higher the probability of newbuilding order. Various challenges in shipbuilding also form an 'uncertain part' that always looms in the forecasting of newbuilding order. In econophysics, uncertainty is mostly dealt with a coherent manner appreciating other factors, and concerned data on the factors. The uncertainty reduces also with the improvement of the models (Chen, 2017, Dionisio et al., 2006, Schinckus, 2009). As such, applying econophysics approach to forecasting not only adds value as a pioneering tool to shipbuilding forecasting but also provide an insight on the 'uncertainty part' in the newbuilding order forecasting.

Overall, the force that drives the shipbuilding order forms through the constructs such as freight rate, international seaborne freight task, scrap price, newbuilding price index, the share of scrapable ships of age 20 and above, existing fleet, new ship delivery and ship demolition. This forms a reasonable set of factors or constructs to develop the predictors of this study; other factors have not been accommodated into the predictors mainly either due to the relational distance to predictors or non-availability of quality data. In context of the above discussion, the next section illustrates the methodology of this research.

3. Econophysics Methodology

The application of the theories of physics in economics or business is rapidly evolving and proves efficient in many complex market scenario (Jovanovic and Schinckus, 2016, McCauley, 2004, Schinckus and Jovanovic, 2013, Zapart, 2015). The new shipbuilding market is a complex dynamics where shipbuilding order is gravitated by the force between two critical masses: the 'existing shipping market prospect' and ship's age-adjusted 'future shipping market prospect' (Stopford, 2009, Bruce and Garrard, 1999, UNCTAD, 2018a, Steidl et al., 2018). This force can indicate the thrust for new shipbuilding order that resembles the force of gravity in physics. With this notion, this study assumes an econophysics approach of forecasting new bulk shipbuilding order by adopting and naturalising Newton's law of gravitation (see equation 1). Figure 4 presents a logical framework of this methodology.

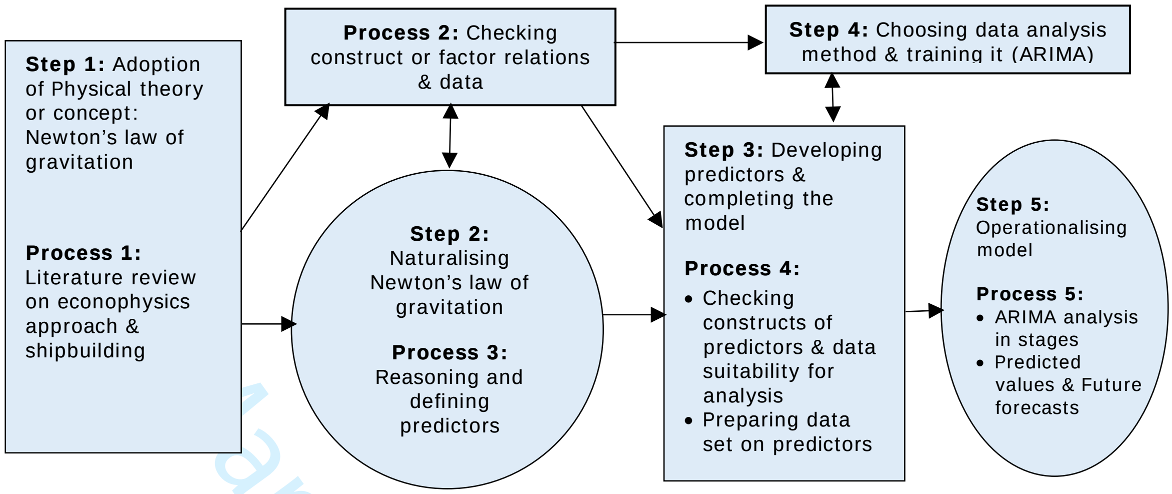


Figure 4: Logical framework of the econophysics methodology of this study delineating steps and processes

The developed model is then investigated within a data set between the years 2008 and 2017. This period is chosen as all required data of the variables and constructs (that form the independent variables for the econophysics model) are available and easily accessible. The easily accessible data enhances the convenience of utilizing the model. However, the multivariate Auto-Regressive Integrated Moving Average (ARIMA) analysis is adopted to examine the forecasting model. The multivariate ARIMA has been chosen as it captures a set of various standard temporal constructs in the time series data (Gujarati, 2003, Tabachnick and Fidell, 2007, Duke University, 2018) which is the case for this shipbuilding order forecasting through econophysics approach. In other words, the ARIMA statistical analysis technique well suits with the complexity of the new shipbuilding market. The rest of this section depicts the development of the model and illustrates the data.

Newton's law of gravitation in physics is expressed as follows:

$$F = G\frac{M_1 * M_2}{d^2} \qquad (1)$$

where, 'F' denotes the force between the two objects 'M_1' and 'M_2'
'M_1' indicates the mass of one object
'M_2' indicates the mass of the other object
'd' refers to the distance between the two objects and
'G' indicates the gravitational constant

Resembling Newton's law of gravitation, the force for the new bulk shipbuilding order is framed as follows:

$$Sb_{OB} = U_B\frac{B_{fr} * B_{fp}}{{d_B}^2} \qquad (2)$$

where,
'B_{fr}' indicates the existing bulk shipping market prospect
'B_{fp}' indicates the future bulk shipping market prospect
'Sb_{OB}' refers to the force between 'B_{fr}' and 'B_{fp}' and indicates the new shipbuilding order
'd_B' refers to the distance between 'B_{fr}' and 'B_{fp}' indicated by the fleet evolution
'U_B' indicates the uncertainty constant for the concerned newbuilding shipping market

For simplicity, replacing ${d_B}^2$ *by* d_{Bsq} and assuming the value of U_B in equation (3) as 1 (binary one) to recognise the presence of uncertainty (which later will be evolved as the unexplained variance of the dependent variable during ARIMA analysis) equation (3) is expressed as follows:

$$Sb_{OB} = \frac{B_{fr} * B_{fp}}{d_{Bsq}} \qquad (3)$$

The orientation and constructs of the dependent variable (Sb_{OB}) and relevant independent variables (B_{fr} , B_{fp} and d_{Bsq}) of this econophysics model for bulk shipbuilding forecasting in equation (3) have been further elaborated in Table 1.

Table 1: Naturalizing the variables of econophysics model for new bulk shipbuilding order forecasting

Variables of the proposed econophysics model – $Sb_{OB} = \frac{B_{fr} * B_{fp}}{d_{Bsq}}$	**Proposed constructs of the variables in bulk shipbuilding forecasting model**
$\boldsymbol{B_{fr}}$ → the existing bulk shipping market prospect.	▪ It can be measured by the product of 'bulk freight rate (B_{BDI})[the Baltic Dry Index (BDI) is used]' and the 'international seaborne main bulk freight task (B_{IST})'. ▪ The data sources are the Clarkson database for B_{BDI} and UNCTAD report (analysis based on Clarkson database) for B_{IST}.
$\boldsymbol{B_{fp}}$→ the future bulk shipping market prospect	▪ It can be measured by the product of the percentage share of bulk ships age of twenty and above (B_{TWA})' and 'the ratio between the average bulk ship scrap price (B_{SCRP}) and shipping newbuilding price index (B_{NBPI})'. ▪ The data sources include the Clarkson database for B_{NBPI} and UNCTAD report (analysis based on Clarkson database) for B_{TWA} and the report of the French based brokers house the Barry Rogliano Salles (BRS) Group (analysis based on Clarkson database) for B_{SCRP}.
$\boldsymbol{d_{Bsq}}$ → the square of the distance between 'B_{fr}' and 'B_{fp}	▪ It is measured by the 'fleet evolution in the bulk shipping market'. ▪ The fleet evolution of the bulk market is further determined by the summing 'existing bulk fleet (B_{FLT})' with the 'new delivered bulk fleet (B_{NDEL})' and then subtracting the 'bulk fleet demolition (B_{DEMO})' from the summation. ▪ The data sources for all three constructs (B_{FLT} ,B_{NDEL} , B_{DEMO}) are several reports of the French based brokers house the Barry Rogliano Salles (BRS) Group (analysis of which are based on Clarkson database).
$\boldsymbol{Sb_{OB}}$ → the force between 'B_{fr}' and 'B_{fp}' that indicates bulk carrier new shipbuilding order	▪ This is the target or dependent variable that will be forecasted in this study for new bulk shipbuilding order. ▪ The data sources for this variable (Sb_{OB}) include several reports of the French based brokers house the Barry Rogliano Salles (BRS) Group (analysis based on Clarkson database).

Based on the proposed variables and constructs of the variables presented in Table 1, the equation (3) finally takes the following overarching form:

$$Sb_{OB} = \frac{\overbrace{(B_{BDI} \text{ X } B_{IST})}^{B_{fr}} \text{ X } \overbrace{[(B_{TWA} \text{ X })\text{X}\left(\frac{B_{SCRP}}{B_{NBPI}}\right)]}^{B_{fp}}}{\underbrace{(B_{FLT} + B_{NDEL} - B_{DEMO})^2}_{d_{Bsq}}} \qquad (4)$$

where,

'B_{BDI}' indicates bulk freight rate
'B_{IST}' indicates the 'main bulk' international seaborne freight task
'B_{TWA}' indicates the share of bulk carriers of age 20 and above
'B_{SCRP}' indicates bulk carrier average scrap price
'B_{NBPI}' indicates bulk carrier newbuilding price index
'B_{FLT}' indicates the bulk carrier existing fleet
'B_{NDEL}' indicates bulk carrier new delivery
'B_{DEMO}' indicates bulk carrier demolition

In this proposed model, the relationships of the dependent variable, Sb_{OB} (the new bulk shipbuilding order) with the independent variables (B_{fr} , B_{fp} and d_{Bsq}) play a significant role in naturalizing with the econophysics approach (in this case, the use of Newton's law of gravitation). Further elaborating on this naturalising aspect, it is to state that the new bulk shipbuilding order sits at the crossroad between the demand and supply. In other words, it balances two loops such as the supply-side capacity adjustment loop and the demand-side capacity utilisation loop (Randers and Göluke, 2007). The increase in shipping capacity (supply or fleet evolution) can decrease capacity utilisation efforts or demand meeting efforts (in this case, new shipbuilding order). The fleet evolution also creates the distance (d_B) between the 'existing bulk shipping market prospect' and 'future bulk shipping market prospect'. Hence, inversely proportional relation exists between the fleet evolution [i.e. (existing ships+new deliveries–ship demolitions), later squared and expressed as d_{Bsq}] and the new bulk shipbuilding order (Sb_{OB}).

On one hand, the conjugate momentum of ascending or descending freight rate and international seaborne freight task increases or decreases the new shipbuilding order prospect respectively (DSF, 2018, Stopford, 2009). The international seaborne freight task is a direct reflection of the global economic growth in maritime business, while the global economic growth increases global trade and in-turn the international seaborne freight task, which is a derived demand of the trade (UNCTAD, 2018b). Hence, the 'existing shipping market prospect (B_{fr})' as a product of the 'freight rate' (in this case the BDI) and 'international seaborne freight task' is directly proportional to the new shipbuilding order (Sb_{OB}). On the other hand, new shipbuilding ordering activity not only focuses on future shipping market prospect but also regarded as a replenish activity of ship demolition. The older vessels are first considered for ship demolition. In any ship category, the percentage share of the ships of 'age twenty and above' is sensitive to demolition particularly in the context of emissions reduction related emerging technology adoption possibility. However, this age range (twenty and above) covers greater and nearly exhaustive list of probable bulk scrap candidates. Besides this, the right time for demolition is when the scrap price is higher. Hence, the 'ratio between the average scrap price and new shipbuilding price indices' with a multiplier of 'twenty and above age ships' captures the 'prospect of future new bulk shipbuilding market $(B_{fp})'$ and is directly proportional to the new shipbuilding order (Sb_{OB}).

However, forecasting new shipbuilding order is complex and involves constructs that can be significantly influenced by the behaviour of the market players. This attitude or behaviour is sometimes unexpected and not predictable (Stopford, 2009) and may arise because of different viewpoints of the market players on international regulatory, business and operational environment. Therefore, the unpredictable part of the new shipbuilding order forecasting may appear as an unexplained variance of the dependent variable. The data for this study is collected from various sources such as the Clarkson data, the UNCTAD's reports and database, OECD reports and the reports of the French-based brokers house the Barry Rogliano Salles (BRS) Group. The data of Clarkson, UNCTAD, OECD and BRS have been used because they are very much maritime focused and the data references are adjusted every year based on the availability of actual data of immediate previous years rather than depending on estimated data. The UNCTAD, OECD and BRS data and their analyses are also in most cases based on Clarkson database that in-turn ensures homogeneity of the data sources and enhances the generalizability and acceptability of the data.

The data for this study has been gathered over the period from 2008 to 2017. This period (2008-2017) has been chosen because of the optimal availability of quality data on all required constructs of the models for bulk carrier newbuilding forecasting. Though yearly data is prevalent and easily accessible rather than monthly data, monthly data is more essential to comprehend the insights of the market dynamics through statistical analysis. Based on the availability, the monthly data collection has been prioritised and later in case of absence of monthly data the yearly data has been interpolated over the selected period in various ways based on the characteristics of the data. Because of the interpolation of the yearly data, which is a frequent practice in forecasting (Zhao et al., 2019, Tokumitsu et al., 2015) and even in simulation and data generation (Li et al., 2020), the outliers in the data set have been eroded automatically before starting the analysis. Aligning or removing outliers as a logical pre-processing step of data analysis brings in benefits by avoiding a few bad apples that may spoil the entire bushel (Cant and Xu, 2020, Shah and Patil, 2019, Lyutikova and Shmatova, 2020).

Table 2: The yearly data on the fundamental constituents of the variables on bulk shipbuilding forecasting

Year	Sb_{OB} (in M dwt)	B_{FLT} (in M dwt)	B_{NDEL} (in M dwt)	B_{DEMO} (in M dwt)	B_{BDI} (Index)	B_{IST} (in Bill Ton-Miles)	B_{TWA} (in % of total dwt)	B_{SCRP} (yearly average in $US/ Long Ton)	B_{NBPI} (Index)
2008	85.4	391.13	28.9	0.48	6344.98	10476	30.30	452.5	191
2009	23.4	418.36	22.47	1.37	2612.47	11006	28.80	275.4	162
2010	88.5	456.62	79.55	0.76	2759.71	12336	27.40	390.4	150
2011	39.7	532.04	53	2.5	1546.61	13019	23.50	484.6	140
2012	24	623.01	54.24	3.54	923.67	14099	17.60	426.3	135
2013	75.4	686.64	34.55	2.3	1213.88	14764	11.00	398.8	125
2014	57	728.32	26.72	1.66	1104.17	15828	9.65	431.3	122
2015	33.8	761.78	26.76	2.89	712.66	15897	8.99	335.6	115
2016	16.3	779.29	25.93	3.04	675.81	16314	8.04	254.2	121
2017	39.2	795.52	21.05	1.43	1152.61	17217	7.01	354	125

The monthly data have been used finally for the ARIMA analysis for bulk new shipbuilding order forecasting. The ARIMA analysis model has been used as it has the capability of explaining a given irregularly patterned time series based on its own lags (Ohyver and Pudjihastuti, 2018, Duan and Zhang, 2020), which is the case for several time series used in this study. Due to the vastness of the monthly data, the yearly data have been presented in Table 2 to provide a glimpse of the data requirement of this study. Usually, the data are demonstrated in different units in different reports. For the sake of analysis and to provide an even footing for the model, the data in this study have been either synchronised in similar units or created indices through normalisation, taking logarithm or converted in percentage share. The data shows a moderate cyclical nature of about 36 months or 3 years that has been declared during preparing the ARIMA analysis technique through the SPSS.

4. Data Analysis and Discussion

In this multivariate ARIMA analysis, there are three predictors or independent variables (B_{fr}, B_{fp} and dB_{sq}) for one dependent or outcome variable [the new bulk shipbuilding order (Sb_{OB})]. During fitting the analysis model for multivariate ARIMA through the SPSS software, the econophysics model of this study (see equation 4) has been ensured by assigning the variables as numerators (for B_{fr} and B_{fp})

and denominator (for dB_{sq}). The analysis has been completed in four stages such as 1) Checking data assumption and identification of models, 2) model estimation and selection, 3) diagnosis and validation, and 4) forecasting and discussion.

4.1 Checking data assumption and identification of models

Before data analysis, the normality and stationarity of the data have been checked and found that log data of the variables are required to ensure normality (see Figure 5 and Table 3). Figure 5 shows a strong dependence of variability of the bulk shipbuilding order and indicates the necessity of data transformation, for example, logarithmic transformation to stabilise the variance. Table 4 depicts the detail normality tests of the variables.

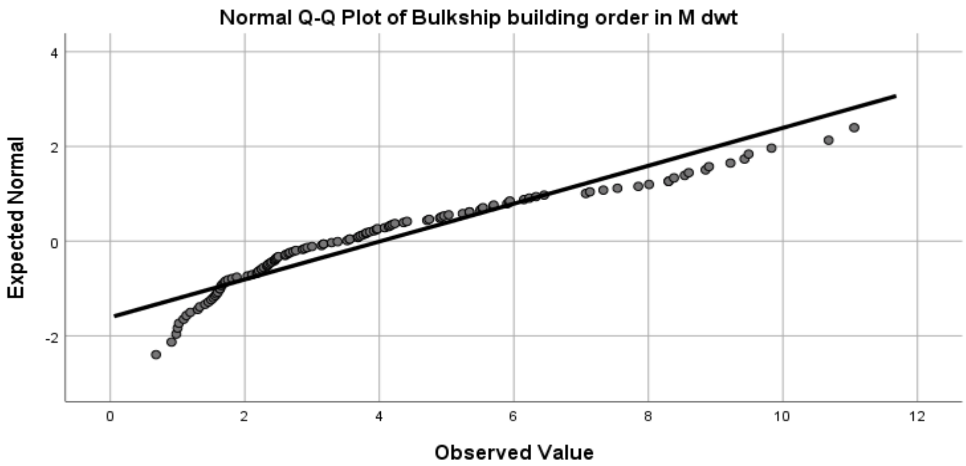


Figure 5: Normality test of the dependent variable bulk shipbuilding order (Sb_{OB}). Source: SPSS output

Table 3: Indication of the requirement of achieving normality and stationarity of the variable parameters

	Skewness	Kurtosis	Mean (Std. Error)	Variance	Std. Deviation
Sb_{OB}	.752	-.405	4.451 (.261)	6.532	2.558
B_{fr}	2.210	6.158	25967904.519 (2280497.876)	499264373995425.200	22344224.623
B_{fp}	2.476	6.962	63.595 (6.069)	3536.063	59.465
dB_{sq}	1.140	.520	389081.537 (31302.547)	94065544849.836	306701.068

Table 4: Necessity of ensuring normality of the Bulk shipbuilding forecasting variables through log transformation [based on monthly 'Testing data set' (2008-2015)]

Test → / ↓ Variables	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistics	df	Sig.	Statistics	df	Sig.
Sb_{OB}	.118	96	.002	.922	96	.000
Log of Sb_{OB}	.068	96	.200*	.974	96	.054
B_{fr}	.193	96	.000	.767	96	.000
Log of B_{fr}	.085	96	.083	.980	96	.159
B_{fp}	.207	96	.000	.721	96	.000
Log of B_{fp}	.061	96	.200*	.980	96	.153
dB_{sq}	.151	96	.000	.877	96	.000
Log of dB_{sq}	.050	96	.200*	.981	96	.170

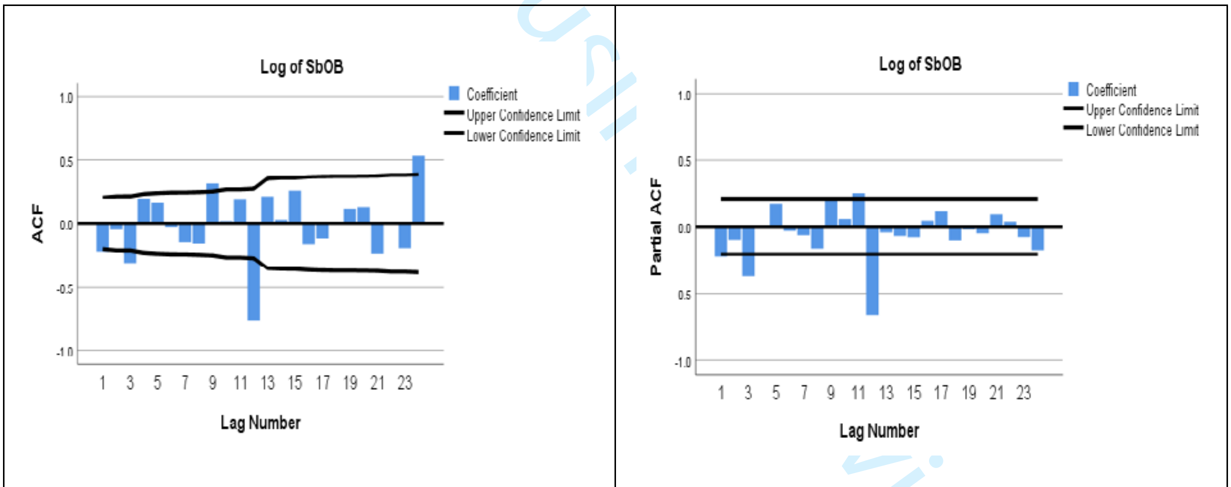
a. Lilliefors Significance Correction
*. This is a lower bound of the true significance.

As an assumption of the ARIMA analysis, the stationarity of the dependent variable needs to be ensured (Gujarati, 2003, Tabachnick and Fidell, 2007), which has been taken care of in this study by taking the first difference of the dependent variable (Sb_{OB}) during performing the ARIMA analysis through the SPSS (Statistical Package for the Social Sciences) software version 25. The requirement of taking the 1st difference of the dependent variable during ARIMA analysis of this study (Sb_{OB}) is also evident from the descriptive statistics as shown in Table 4.

As a common rule for the non-normal actual dependent variable, it is important to ensure more than twenty records for each independent variable (Tabachnick and Fidell, 2007). In this study, five years (2008-2012) monthly data have been used as a training data set. Later, eight years of monthly data (2008-2015) have been used as the testing data set. This testing data set has been emphasised for model selection and estimation as it ensures adequate data points such as 96 records for each series. The monthly data from 2016-2017 is used during the validation stage. Finally, ten years of monthly data (2008-2017) have used for predicted values and future forecasting. The detail of the ARIMA analysis in four stages is provided below.

4.2 Model estimation and selection

The autocorrelation function (ACF) and partial autocorrelation function (PACF) have been generated on the testing data set to estimate the tentative ARIMA models. Figure 6 shows the correlograms of ACF and PACF of the log transformed bulk shipbuilding orders (Log of Sb_{OB}) at the first non-seasonal differencing. Although the Lag spikes are within the 95% confidence level, some spikes are still showing that significant information is contained and there is a tendency of correlations.



(a) Auto-correlation function of Log of Sb_{OB} | (b) Partial Auto-correlation function of Log of Sb_{OB}

Figure 6: Initial correlograms of Log of Sb_{OB} at the first non-seasonal differencing

Based on the significant closest lag spikes both in the ACF and PACF correlograms (i.e. Lag1,3,9 and 12), the ARIMA models (1,1,3), (3,1,1), (1,1,9), (9,1,1), (3,1,9) (9,1,3), (12,1,1), (12,1,3), (12,1,9) and (12,1,12) are selected tentatively and run. As usual, the distance lag spikes are deliberately ignored initially (such as Lag24) to avoid model over-fitting but later considered to achieve a stingy or parsimonious model. The outcome criteria (indicated in column 1 in Table 5) of the tentative models are summarised in Table 5. The expectations of the criteria values of the models are indicated in Column 2 in Table 5. Mainly the values on the criteria such as the Stationary R-squared (the indicator of the variance captured by the dependent variable), Normalized BIC (Bayesian Information Criteria) Index (designed to choose between models as its lower value is better), and Mean Absolute Error (MAE, the lower value is better) are used to select a model.

The (12,1,1) ARIMA model has been selected as most appropriate to perform the diagnostic. This model has been selected as appropriate because it meets all expectation (column 2 in Table 5) particularly the normalized-BIC is the lowest with significance level .068 (>.05).

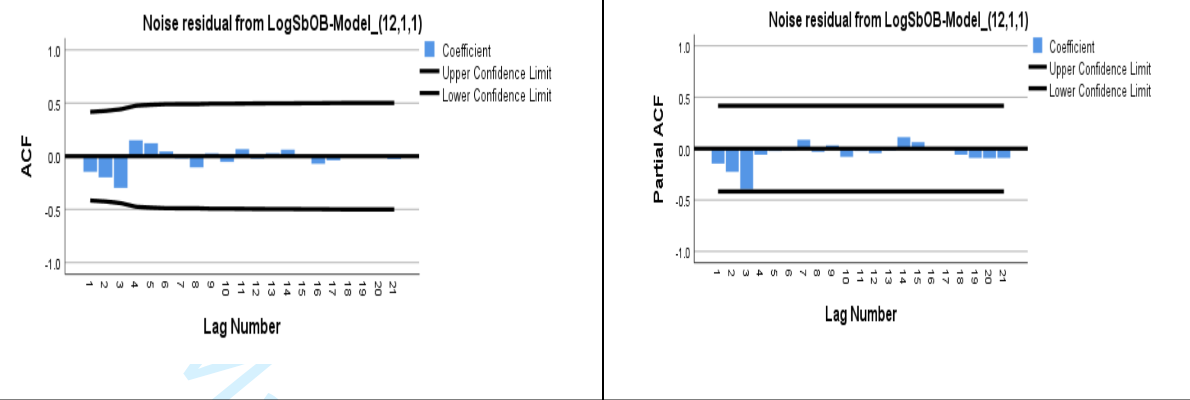
Table 5: The tentative models with their comparable criteria values

Model selected →		Arima (1,1,3)	Arima (3,1,1)	Arima (1,1,9)	Arima (9,1,1)	Arima (3,1,9)	Arima (9,1,3)	Arima (12,1,1)	Arima (12,1,3)	Arima (12,1,9)	Arima (12,1,12)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
↓ Criteria	↓ Expectation										
Stationary R-squared	Higher value	.187	.225	.443	.316	.528	.594	.726	.728	.774	.785
R-squared	Higher value	.479	.503	.643	.561	.697	.740	.824	.825	.855	.862
RMSE	Lower value	.199	.194	.171	.190	.159	.148	.122	.124	.118	.117
MAPE	Lower value	56.790	59.993	46.597	47.446	38.377	38.614	30.554	30.619	30.021	29.915
MaxAPE	Lower value	2471.260	2881.671	1709.349	2027.033	1498.643	1708.299	1524.565	1531.075	1389.177	1363.536
MAE	Lower value	.139	.135	.126	.125	.107	.097	.066	.067	.068	.068
MaxAE	Lower value	.617	.649	.369	.704	.519	.493	.459	.458	.383	.360
Normalized- BIC	Lower value	-2.701	-2.749	-2.716	-2.512	-2.761	-2.912	-3.242	-3.127	-2.940	-2.802
Ljung-Box Statistics (Sig.)	Lower value (Sig. should be > (.05)	71.371 (.000)	57.422 (.000)	48.015 (.000)	65.728 (.000)	49.334 (.000)	57.920 (.000)	10.283 (.068)	11.947 (.008)	- (-)	- (-)
Constant Estimate (Sig.)	Lower value (Sig. should be > (.05)	-.480 (.515)	-.591 (.363)	-.746 (.160)	-.696 (.306)	-.650 (.292)	-.648 (.253)	-.003 (.995)	-.003 (.994)	-.322 (.416)	-.659 (.072)

4.3 Diagnosis and validation

For diagnostic purpose, the residual analysis of the selected appropriate model (12,1,1) has been performed and shown as correlograms in Figure 7. The correlograms on noise residuals are decaying within the 95% confidence level; however, lag24 indicates that there may be some information remaining to capture. From the initial correlograms on the Log of Sb_{OB} (Figure 6), it is also evident that the distant lag24 both in ACF and PACF may have potential to capture the remaining information which ultimately necessitates adjusting for the most appropriate model by investigating additional models with lag24. Emphasising on the lag24, the additional ARIMA models (12,1,24), (24,1,12), (24,1,9), (24,1,3) and (24,1,1) are selected for further diagnostics. This process ultimately ensures avoiding over-fitting and reaching to a most parsimonious or stingy model. Running these additional models and comparing the criteria values with the appropriate model selected earlier (i.e. model 12,1,1) provide the best model.

As presented in Table 6, the further diagnostic outcomes show that (12,1,1) is still the best model because of its generated Ljung-Box statistics with significance level >.05 (Sen et al., 2016) and its lowest normalized-BIC value. The other additional models mainly could not generate the required Ljung-Box statistics. The best model (12,1,1) is then run on a different set of data (Monthly data of 2016-2017) for the validation.



(a) The ACF of the residuals of ARIMA (12, 1, 1) model on validation data set (Monthly 2016-2017)	(b) The PACF of the residuals of ARIMA (12, 1, 1) model on validation data set (Monthly 2016-2017)

Figure 7: Correlograms of noise residuals from $LogSb_{OB}$ of ARIMA model (12, 1, 1)

Table 6: The outcome criteria values of the further diagnostic models

	Model selected →	Arima (12,1,1)	Arima (12,1,24)	Arima (24,1,12)	Arima (24,1,9)	Arima (24,1,3)	Arima (24,1,1)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
↓ Criteria	Expectation						
Stationary R-squired	Higher value	.726	.770	.782	.809	.795	.798
R-squared	Higher value	.824	.852	.860	.878	.868	.871
RMSE	Lower value	.122	.135	.131	.119	.117	.115
MAPE	Lower value	30.554	30.949	29.986	26.598	26.582	27.565
MaxAPE	Lower value	1524.565	1407.358	1412.571	1200.166	1193.314	1245.573
MAE	Lower value	.066	.073	.069	.064	.066	.065
MaxAE	Lower value	.459	.314	.374	.322	.346	.352
Normalized- BIC	Lower value	-3.242	-1.949	-2.001	-2.336	-2.655	-2.799
Ljung-Box Statistics (Sig.)	Lower value (Sig. should be > .05)	10.283 (.068)	- (-)	- (-)	- (-)	- (-)	- (-)
Constant Estimate (Sig.)	Lower value (Sig. should be > .05)	-.003 (.995)	-.664 (.208)	-.665 (.163)	-.636 (.051)	-.669 (.013)	-.316 (.175)

The model statistics and a summary of the validation run are shown in Tables 7 and 8. The model captured about 65.6% variance of the dependent variable through the three predictor variables. Therefore, the uncertainty appeared as the unexplained variance of about 34.4%. The Ljung-Box stat is reasonable with the significance level >.05. The ACF and PACF of the noise residual from the dependent variable are also decaying (or flat) within the 95% confidence level as expected for a good model (shown earlier in Figure 7).

Table 7: Model statistics on the validation data set (Monthly 2016-2017)

Model Statistics						
		Model Fit statistics		Ljung-Box Q(18)		
Model	Number of Predictors	Stationary R-squared	Normalized BIC	Statistics	DF	Sig.
Log of SbOB_Model(12, 1, 1)	3	.656	.660	7.111	5	.213

Table 8: Model summary on the validation data set (Monthly 2016-2017)

Model Summary	
Fit statistics	Mean
Stationary R-squared	.656
R-squared	.708
RMSE	.356
MAPE	107.391
MaxAPE	1081.509
MAE	.094
MaxAE	.287
Normalized BIC	.660
Ljung-Box Statistics (Sig.)	7.111 (.213)
Constant Estimate (Sig.)	-2.198 (.806)

As the model (12,1,1) well-performed in the validation stage, this model is then used for bulk shipbuilding forecasting with the ten years' monthly data (2008-2017).

3.4 Forecasting and discussion

At the forecasting stage, the model (12,1,1) captures 73.3% variance of the dependent variable through the three predictor (independent) variables in the study. The Ljung-Box statistics is also good with the significance level >.05, as demonstrated by other empirical study (Sen et al., 2016). The model statistics and summary of the forecasting run are shown in Tables 9 and 10.

Table 9: Model statistics on the forecasting data set (Monthly 2008-2017)

Model Statistics						
		Model Fit statistics		Ljung-Box Q(18)		
Model	Number of Predictors	Stationary R-squared	Normalized BIC	Statistics	DF	Sig.
Log of SbOB_Model(12,1,1)	3	.733	-3.427	8.677	5	.123

Table 10: Model summary on the forecasting data set (Monthly 2008-2017)

Model Summary	
Fit statistics	Mean
Stationary R-squared	.733
R-squared	.841
RMSE	.121
MAPE	33.344
MaxAPE	1732.568
MAE	.066
MaxAE	.417
Normalized BIC	-3.427
Ljung-Box Statistics (Sig.)	8.677 (.123)
Constant Estimate (Sig.)	-.222 (.571)

Overall, the analysis of this study presents a good fit for an ARIMA model. The ARIMA (12,1,1) model performs well for forecasting the new bulk shipbuilding order (see Figure 8). The three independent variables formed by utilising the econophysics approach (i.e. the law of gravitation) support capturing about 65-73% variance of the dependent variable (i.e. the new bulk shipbuilding order) through the ARIMA (12,1,1) model (see Tables 5, 6 and 9). On the one hand, this model can provide a useful tool for deciding on the new bulk shipbuilding order and help investment related risk management. On the other hand, it is needed to be very cautious as the UCL (Upper Confidence Level) and LCL (Lower Confidence Level) values and the analyses of errors on the predicted results are very wide (see columns 4, 5, 6 and 8 of Table 11); though the errors in the percentage of the predicted values to the original values (actual bulk new shipbuilding order) appears to be low (see column 7 of Table 11). Taking into account of the UCL and LCL values for illustrating this ARIMA analysis elevates the quality of the outcomes (Mohamadi et al., 2011)

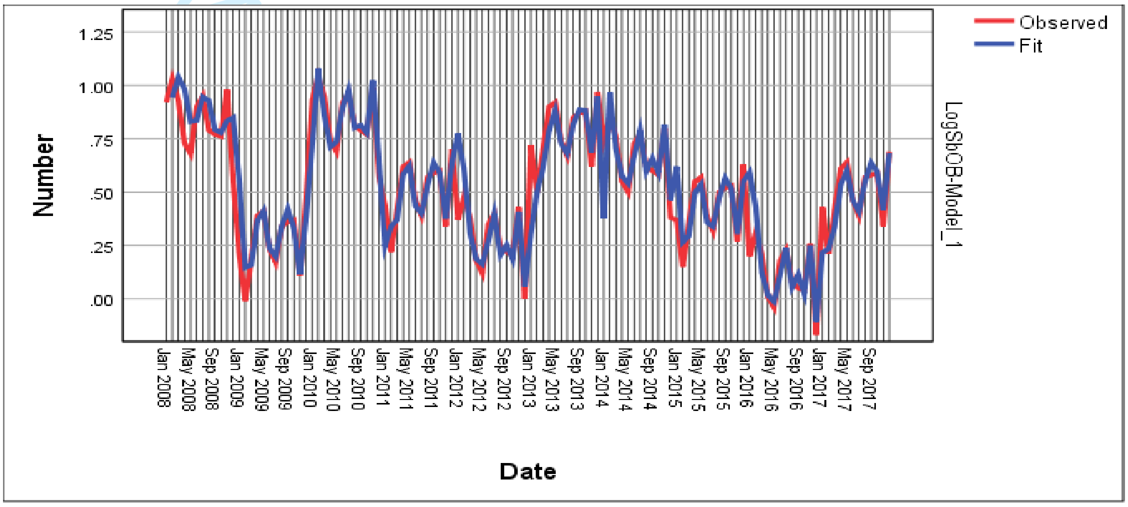


Figure 8: The Fit values of ARIMA (12, 1, 1) model run on the forecasting data set (Monthly 2008-2017)

Table 11: The Fit values of ARIMA (12, 1, 1) model run on the forecasting data set (Monthly 2008-2017)

Year	Original	Predicted	LCL*	UCL**	Error	Error of Predicted values to Original values in %	Probable error of Predicted values in %
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2008	85.40	85.63	32.21	228.37	11.01	-0.27	12.85
2009	23.40	27.32	16.70	44.94	12.49	-16.75	45.71
2010	88.50	81.56	49.83	134.06	12.57	7.84	15.42
2011	39.70	42.63	25.97	69.90	11.44	-7.39	26.83
2012	24.00	24.38	14.86	39.99	13.29	-1.59	54.51
2013	75.40	69.53	42.37	114.04	13.84	7.78	19.91
2014	57.00	57.72	35.31	95.04	11.26	-1.26	19.51
2015	33.80	34.31	20.93	56.34	11.68	-1.50	34.05
2016	16.30	16.99	10.30	27.73	12.28	-4.25	72.26
2017	39.20	35.44	21.58	57.92	11.34	9.59	31.99

* Lower Confidence Level value
** Upper Confidence Level value

The unexplained variance of about 27-35% might have a reflection of the constant of the model (U_B) (see Equation 2 and 3) that initially assumed to be a binary one (1) to recognise the uncertainty part in new bulk shipbuilding order forecasting. This uncertainty is due to the fact that shipbuilding order forecasting becomes a complex issue that plausibly arises from international regulatory, business and ship operation environment that eventually form a variable for behavioural pattern of shipping market players. This unpredictable pattern is very evident in the outcome of future forecast on the bulk shipbuilding order through the ARIMA (12,1,1) model based on the Sb_{OB} monthly data series (2008-2017) [see Figure 9 and Table 12]. For instance, the future predicted value of bulk shipbuilding order in this study for 2018 is 18.33 M dwt with the UCL and LCL values are 52.89 and 6.9 M dwt respectively, whereas an already published report shows that the actual bulk shipbuilding order in 2018 was 48.1 M dwt (BRS Group, 2019). This variable order placement may have occurred due to the changing international regulatory, trade and climate-related operational dynamics in the shipping industry which has different meanings to different investors. However, new bulk shipbuilding order in the 1st half of 2019 is about 73% down in comparison to the 1st half of 2018 (Watkins, 2019); this falling trend seems apparently reflected in the future forecasting for 2019 (see Table 12).

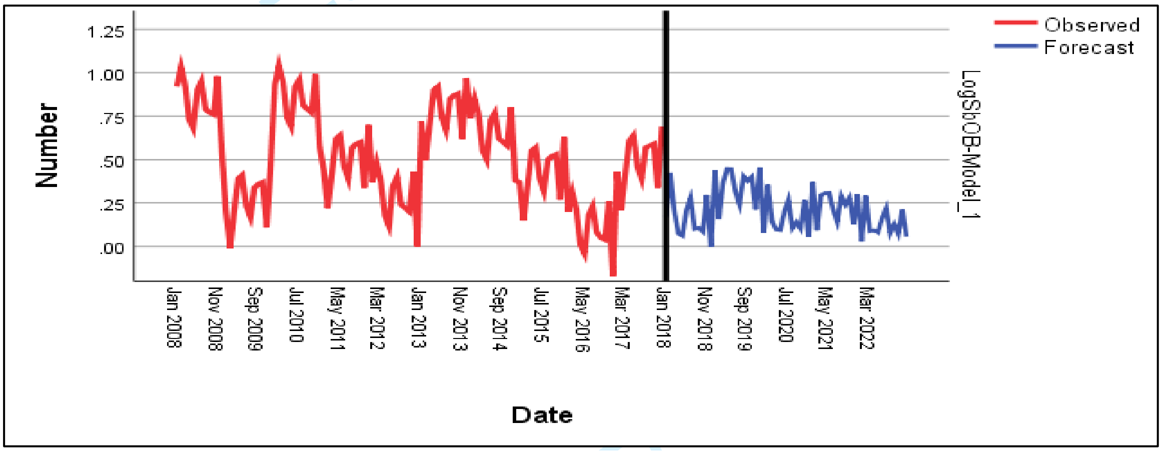


Figure 9: The Observed value and future forecast through ARIMA (12, 1, 1) model run on the Sb_{OB} monthly data (2008-2017)

Table 12: Future forecast for new bulk shipbuilding in ARIMA (12, 1, 1) model run on the SbOB monthly data (2008-2017)

Year	Future forecast for New Bulk shipbuilding order (in M dwt)	UCL** (in M dwt)	LCL* (in M dwt)	Available actual New Bulk Shipbuilding order (in M dwt)
2018	18.33	52.89	6.90	46.4 (Close to UCL)
2019	27.83	120.56	6.43	24.6 (Close to future forecast)
2020	17.69	100.80	3.14	-
2021	21.57	149.96	3.11	-
2022	16.28	137.60	1.93	-

* Lower Confidence Level value
** Upper Confidence Level value

The study reveals an important limitation of the quality of maritime data, which is improving gradually though (World Bank Group, 2019). The lack of quality data may have an impact on the forecasting results. It is found during the construction of the independent (predictive) variables through econophysics approach that most of the publicly available reports utilised the Clarkson database in various ways; the presentation of these data are either not clear or not comparable even among different reports of the same organisation. Mostly the yearly data were available. However, the actual monthly data could reflect a better insight of the industry.

The lack of reliable required data was another limitation, for example, the absence of reliable bulk carrier's speed related data which could improve the distance variable (d_{Bsq}) of this study. In drawing resemblance to the law of gravity, the incorporation of bulk carrier's monthly speed data as a multiplier could better reflect the distance (d_{Bsq}) between the 'existing bulk shipping market prospect (B_{fr})' and the 'future bulk shipping market prospect (B_{fp})'. This improvement is noticeable while lower speed creates demand for more shipping capacity and vice versa. However, the improvement of the independent variables may bring more reliable forecasting results in future through this model. This inherent opportunity to improve variables eventually ensures the robustness of the econophysics based ARIMA (12,1,1) model. Another limitation of this study is related to the emissions reduction efforts from international shipping. On the one hand, the efforts of reducing emissions from shipping would reduce the demand of resources such as coal consumption, which in turn may impact the bulk shipbuilding sector. On the other hand, the requirement of automation and change of the propulsion system may increase new bulk shipbuilding order. Though these two diverse impacts scenario may have a balancing or nullifying impact on the bulk shipbuilding order, this has not been captured in this forecasting study as there were lack of relevant data.

5. Conclusion

An effective shipbuilding order forecasting is a trailblazing task that relates to many internal and external factors. The literature review of this study illustrates the constructs of the shipbuilding market and reveals a moderate cyclical nature in the bulk shipbuilding order forecasting. The manifestation of the moderate cyclical nature of shipbuilding (within the period 2008-2017) has been informed in preparing the ARIMA technique to evaluate the econophysics based bulk shipbuilding order forecasting model of this study. Among the main three segments of shipbuilding, bulk shipbuilding order forecasting is worth doing as it is a relatively good indicator of global resources trade that reflects on global production dynamics, and provides an insight into the global economy.

An innovative method of forecasting can enrich forecasting study as well as can provide an opportunity to compare with the other forecasting methods' outcomes. In this context, an econophysics approach has been pioneered in this study to develop a bulk shipbuilding order forecasting model. The flexibility of the econophysics approach is also well suited to complex shipbuilding forecasting where addressing a large number of constructs requires to be accommodated.

The outcomes of the econophysics model indicate a relatively stable good fit. Although relevant maritime data and its quality need to be improved, the flexibility in refining the predictive variables ensure the robustness of this econophysics based forecasting model. However, the uncertainty in the external environment also looms as a critical factor in shipbuilding forecasting that may necessitate investors to keep a cautious look at various exogenous factors such as global maritime regulatory environment, and business environment, and ship's operational environment. It is also worthwhile to state that the interpretation and predictive power of exogenous factors may vary considerably from investors to investors that may inspire in using this flexible econophysics based forecasting model for bulk shipbuilding orderbook.

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