THE DEVELOPMENT OF FORECASTING MODEL FOR DRY BULK SHIPPING BASED ON MARKET BENCHMARKING ON BALTIC DRY INDEX

N. Amiera Johari[1], W.M Dahalan[2], Aminuddin Md. Arof[1], M.Zaifulrizal Zainol[2]

[1]*Maritime Management Section, Universiti Kuala Lumpur, Malaysian Institute of Marine Engineering, Technology Lumut, Perak, Malaysia*

[2]*Marine Electrical & Engineering Section, Universiti Kuala Lumpur, Malaysian Institute of Marine Engineering, Technology Lumut, Perak, Malaysia*

Corresponding email: wardiah@unikl.edu.my

ABSTRACT

The purpose of this research is to develop a forecasting model for freight rate determination in dry bulk shipping based on benchmarking from Baltic Dry Index. The economies of China, India, and Southeast Asia have experienced rapid industrial development, resulting in a large increase in the yearly growth rate of demand for dry bulk commodities. As a result, the freight rate environment was strengthened, and freight rates reached all-time highs. Dry bulk vessels are used in both the spot and long-term charter markets. Spot prices are generally higher than time charter rates. While bigger earnings can be achieved in good markets with higher spot rates, time charters provide a more consistent income stream over a longer period and lessen short-term market volatility. Depending on how a company interprets market trends and its overall corporate strategy, the mix of spot and period employment varies. The Baltic Exchange's Baltic Dry Index (BDI) measures the overall performance of the dry bulk sector and represents the rate development of Capesize, Panamax, and Supramax vessels. On a daily Time-Charter Equivalent (TCE) basis, the industry examines freight rate evolution in both spot market and time charter rates which indicates rates paid to shipping companies each day net of voyage associated expenses that are typically incurred by charterers.

Keyword: *Baltic Dry Index, Freight Market, Chartering, Broking*

1.0 INTRODUCTION

In a globalized world, boundaries are dissolving, and countries pursue their own welfare-enhancing policies. Since no country can be superior in every region, trade between countries is essential. This, in essence, necessitates trade logistics, for which shipping by sea is the most cost-effective approach in terms of cost per unit. Maritime shipping makes foreign trade simpler. For example, China's strong economic growth following its entry into global trade would not have been possible without efficient maritime transport. Sea transport, on the other hand, has its own economic framework. Global trade influences this economic system, which in turn has an impact on global trade. The role of the supply–demand balance is the basis of this interaction.

There are five factors that distinguish the supply and demand sides of shipping. The global economy, seaborne product trades, average haul, random shocks, and transportation costs are all factors that influence demand. The world fleet, fleet efficiency, shipbuilding production, scrapping and losses, and freight revenue are all supply side variables. Freight rates are calculated by the interaction of these factors, and freight rates are at the core of the shipping industry. Freight prices are primarily dictated by economic activity, and developments in the economy have a direct effect on the maritime sector. In terms of risk management and resource utilization, understanding the dynamics and patterns in freight rates is extremely advantageous. In this regard, the economic effect on the maritime industry is unquestionable. Dry bulk markets, on the other hand, are decentralized spot markets in which exporters, importers, and traders must conduct a search in order to rent a ship for a certain itinerary. Dry bulk ships, according to Brancaccio, Kalouptsidi, and Papageorgiou (2020) and others, are the "taxis of the oceans," and their rental prices, or dry bulk freight rates.

The Baltic Dry Index (BDI) reflects freight prices and indicates the overall health of the dry bulk market. Given the importance of this statistic, the research employs a series of leading indicators to increase its prediction ability. The Dry Bulk Economic Climate Index (DBECI) is treated as an exogenous variable and reflects the impact of the most influential economic factors on the dry bulk market. In other words, it is a bespoke indicator and embodies the combined effect of certain elements which stem from the economic environment revolving around the dry market.

This research created a simple model based on the variables of to present econometric explanations of this effect. By empirically checking the supply–demand balance, this study hopes to add to the current maritime economics literature. While it is widely accepted in the literature that freight prices are primarily determined by the intersection of supply and demand, no empirically validated research has been found. It is also considered important for developing sustainable maritime strategies to decide if the supply side or the demand side is more determinant in the creation of freight rates. Through allocating capital in a sustainable way, both transportation companies and transportation customers will contribute to the welfare-increasing effect of global trade. The findings indicate that an increase in demand results in a higher level of price equilibrium, while an increase in supply results in a lower level of price equilibrium. It has also been discovered that improvements in the supply side of maritime transportation have a greater impact on freight prices.

2.0 DRY BULK ECONOMIC CLIMATE INDEX (DBECI)

The DBECI is made up of eight sub-indicators that are theoretically divided into three different driving forces: consumer power, liquidity, and industrial activity. New Residential Construction (US), Euro/USD and Yuan/USD Exchange Rates, Brent Crude Oil Price, Federal Funds Rate, Consumer Credit Outstanding (US), World Industrial Production, Manufacturing and Trade Inventories are the sub-indicators (US).

The aggregation mechanism chosen for the DBECI is an enhanced version of the BOD (Benefit of the Doubt) approach. The BOD (Cherchye et al, 2007) has been used to aggregate multiple sub-indicators in various scenarios of composite indicators. It has been widely used, for example, to compare and rank countries based on their performance. The BOD is based on Data Envelopment Analysis (DEA) (Cooper et al, 2011), which uses linear programming to endogenously determine the relative contribution of sub-indicators by picking the values of the weights associated with them. The BOD assessment identifies the best-performing countries to create a benchmarking border, which the remaining countries use to estimate their maximum relative score. When this methodology is used to time observations rather than countries, it appears that any new observation that enters the assignment issue could be a potential best performance, causing the efficient frontier to shift. As a result of the relative evaluation, the value of the composite indicator for the other observations may change over time, making comparison impossible. To circumvent this flaw, a BOD model extension is employed, which is based on the inclusion of a hypothetical, virtual time observation called "IDEAL." This fictitious time observation corresponds to the best-case scenario of performance. This virtual observation takes precedence over all previous and future time observations, serving as the absolute standard for all time periods, ensuring that the evaluation scores remain consistent across time. Previous research publications have employed the idea of embedding an ideal unit in the set of real units under assessment to rank the efficient units (Wang & Luo, 2006) and extract a common set of weights (Payan et. Al, 2014).

2.1 Estimation of the Composite Indicator

The final set of indicators, namely Narrow Money (M1) (OECD), USA Interest Rates, Federal Funds Rate (US), Shanghai Composite (SSEC), Business Confidence Index (BCI) (G-20), Iron Ore Spot Price CFR N. China, and Construction Spending, are used to estimate the values of the new composite indicator (US).

For the building of the composite indicator, the study adopts and tests three different methodologies which are Geometric Average on grouped indicators and Factor Analysis. The most effective one eventually qualifies for the final version of the DBECI-E to be built. Each of these methods is detailed in detail below.

Assume that the Composite Indicator (CI) scores are the result of the right selection of m individual sub-indicators (X 1, X 2,..., X m) as the primary key elements. T time total observations t = 1,...,T are used to record their values. Let x represent the performance of the indicator X I over time t.

2.2 Geometric Average

To estimate the values of a composite indicator, this method uses a multiplicative formula. In a number of circumstances, it has been advocated for the estimate of composite indicators, including the well-known Human Development Index. The method uses the geometric average formula to calculate higher-level indicators that were previously calculated using other methods, such as simple arithmetic average. Assume that the principal sub-indicators are organized into 1st level indicators, p in number with the to signify the value of indicator I at time observation t. The following is the formula for geometric aggregation:

$$CI_t = \sqrt{[p]}y_{1t}y_{2t}\dots y_{pt}$$

…………………………………………………………………………(1)

In typical additive aggregations, the undesired trait of compensability is removed via the geometric average formula. That is, poor performance in certain measures might be offset by strong performance in others. For composite indicator scenarios where the associated components describe different features of the idea to be measured, geometric aggregation is appropriate.

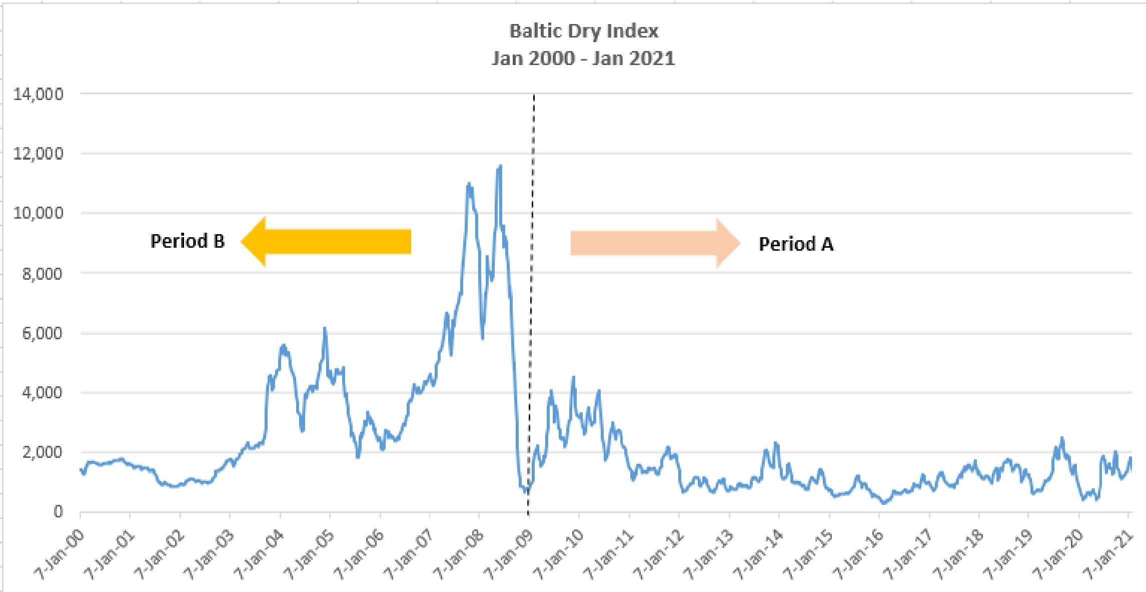
2.3 Factor Analysis

Factor Analysis is a technique for modeling observed variables and their covariance structures in terms of a smaller number of unobservable (latent) "factors." Typically, the components are thought of as broad notions or ideas that can be used to define an event. Most consumption behavior, for example, could be explained by a basic desire to achieve a certain social status. Factor analysis is a type of exploratory/descriptive research that necessitates a lot of subjective judgments. It is a commonly used tool that is frequently contentious due to the flexibility of the models, methodologies, and subjectivity, which can lead to disagreements over interpretations.

The procedure is comparable to principal components, but factor analysis is more involved, as the textbook points out. Factor analysis is, in some ways, a reversal of principal components. The observable variables are modelled as linear functions of the factors in the analysis. The production of new variables that are linear combinations of the observed variables in principal components. The data dimension is lowered in both PCA and FA. Remember that the interpretation of the principal components in PCA is frequently sloppy. On rare occasions, a single variable may play a significant role in more than one of the components. Each variable should ideally contribute significantly to only one of the components. To do this, a technique known as factor rotation is used.

3. RESULTS AND DISCUSSION

For both periods A and B, data were applied for the index aggregating and weighting techniques shown in the methodology. This section describes the results. The methodology was originally used individually with data for periods A and B. Additionally, the models have been applied to the entire data set (A+B) between 2000 and 2021 for comparison reasons.



Graph 1: Baltic Dry Index Values

Initially, seven key factors were identified using the geometric average method in three higher-level indicators. Its results are based on the simple arithmetic format i.e. Y1 = Averages (Narrow Money OECD). Y2 = Average (Iron) = Average, Y3 = Business confidense, Sanghai composite. The composite indicator values are estimated in this case using the following formula;

$$\sqrt[3]{y_{1t}\, y_{2t}\, y_{3t}}\,. \qquad \text{……………………………………………………………………..(2)}$$

Two factors in data sets for periods A and B have been found in the Factor Analysis of selected key factors (A+B). The explained total variance was 78.12, 72.32 and 61.75 percent respectively for periods A, B and A+B.

Table 1: Indicator Weightage

Indicators' weights for time period A	**Indicators' weights for time period B**	**Indicators' weights for time period A+B**
Exchange_rates (0.022)	Fed_Funds (0.335)	Iron (0.135)
Iron (0.374)	US_gulf_wheat (0.082)	SP_GSCI_Commodity (0.200)
TED_spread (0.206)	Japan_Steel_Price (0.142)	Exchange_rates (0.175)
Business_confidence (0.1594)	Narrow_Money_China (0.066)	Consumer_confidence (0.246)
Shanghai_Composite (0.1794)	NASDAQ_Commodity (0.374)	Shanghai_Composite (0.243)

4. CONCLUSIONS

The DBECI-construction aims to capture the key dimensions of the dry bulk freight market's economic environment. In this vein, the creation of this new composite indicator aims to track the overall impact of various economic factors on dry bulk freight rates. The proposed index is made up of three sub-groups of variables, each of which represents a different aspect of the dry cargo market's economic environment.

The empirical analysis investigates whether the proposed index has any causal impact on the market in dry bulk freight. The results of Granger causality and several other statistical tests confirm that DBECI-E causes the BDI significantly. In summary, building a new, dry bulk freight composite indicator could be helpful in monitoring the impact of economic freight rates at greater precision by ship operators and other maritime professionals. This Index could be used as an input to models of freight forecasting as an insight into the macroeconomic developments of special interest.

REFERENCES

[1] Alizadeh-M, AH, Nomikos, NK. (2002). The Dry Bulk Shipping Market

[2] B.Yildiz, U.Bucak. (2017). Determinants of Freight Rates: A Study on the Baltic Dry Index

[3] Carol.M (2021). Baltic Dry Index

[4] D.D Thomakos, J.Liu. (2017). The Baltic Dry Index: Cyclicality, Forecasting and Hedging Strategies.

[5] D. S. Jacks, M.Stuerner. (2021) Dry Bulk Shipping and the Evolution of Maritime Transport Costs

[6] G.I. Batrinca, G.S. Cojanu. (2014). The Determining Factors of the Dry Bulk Market Freight Rates

[7] K. Ozden, S. Ozlen, A.Acik. (2019). Supply-Demand Interaction in the Formation of Freight Rates

[8] Kevin Hill. (2020). What is freight forecasting

[9] Martin Stopford. (2018). Maritime Economics London Routledge

[10] N.Roussanoglou. (2020). Dry Bulk Market’s Fundamental Different Than Six Months Ago

[11] Nov 2015 Demand and supply of maritime transport services: Analysis of Market Cycle

[12] Okan Duru. (2010). A fuzzy integrated logical forecasting model for dry bulk shipping index forecasting

[13] Q.Zeng, C.Qu, A.K.Y Ng, X.Zhao. (2016). A New Approach for Baltic Dry Index Forecasting Based on Empirical Mode Decomposition and Neural Networks

[14] P. Baltyn. (2016). Baltic Dry Index as Economic Leading Indicator in the United States

[15] R.Ekawan. (2006). The evolution of hard coal trade in the Pacific Market

[16] Su Ziyun. (2006). Analysis of the spillover effect between the Baltic Shipping Price Index (BDI) and the International Market Index. Zhongyuan