

Revisiting the impact of the economic environment on the shipping market: The Dry Bulk Economic Climate Index

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Abstract

The present study focuses on the construction of a composite leading indicator which is tailored to the dry cargo market and mirrors the aggregate impact of some carefully selected economic variables. Unlike conventional approaches, the structure and the weighting scheme of this index are based on extensive exploratory and numerical analysis. The linkages between this new indicator and the dry bulk freight rates are investigated by means of Co-integration analysis, Granger Causality tests and Impulse Response analysis. Overall, the results confirm that the proposed index can successfully narrow down the overarching impact of the economic environment and embody the forces directed at the dry bulk freight market. Maritime practitioners may find this new indicator particularly useful, both as a tool to gauge macroeconomic developments of special interest and as an input to predictive models.

Keywords: Composite leading indicator; freight market; dry cargo; causality; economic environment

1. Introduction

The exploration of the environmental context of shipping has always been a challenging endeavour. From a systems perspective, the elements of the shipping industry interact with the economic dimension of its general environment. The relevant literature points out that the impact of the economic environment is ongoing, yet somewhat diffuse.

The key idea of this study is to pinpoint a set of macroeconomic factors that have a theoretical connection with the dry bulk trade and capture their aggregate impact through a pertinent index. This is accomplished through the construction of a new composite indicator, which encompasses some selected economic variables and reflects their effect on freight rates. The Dry Bulk Economic Climate Index (DBECI) is built using only those economic variables that have a profound linkage to the freight market. In this regard, their appropriate combination forms a leading indicator (the DBECI) which is designed to signal economy-driven changes in the dry cargo freight market.

A major characteristic of the world economy is its cyclicity, which is compatible with the cyclical behaviour of the shipping market (Stopford, 2009). On top of this, shipping cycles are frequently driven by economic cycles, reflecting the close ties of the demand for bulk carriers with the state of the economy. This cyclical process is occasionally precipitated by random economic shocks, which usually have large-scale effects. These rare but sudden disturbances cause substantial changes in the demand for shipping services, affecting the level of the freight rates quite dramatically.

The high complexity of the world economy requires a painstaking process of analysing its fundamental factors. China and the US, the world's largest economies, have a tremendous impact on the dry bulk trade. Especially the import and export demand of China - the leading trade nation - is a major driver of freight rates for the entire market. From this perspective, indicators related to the world economy are not necessarily linked to the dry bulk market, considering that they incorporate economic data of several countries that do not trade by sea. Therefore, it is preferable to use those more targeted metrics and thereby ensure to some extent that the sample is impervious to outliers.

The impact of the global economy on the dry bulk freight market has been overly evident over the course of shipping history.

The Wall Street Crash of 1929 and the subsequent great depression of 1930s set off a prolonged shipping recession, which translated into a sharp drop of trade volume and a large number of lay-ups.

The global economic conditions deteriorated again in 1997, due to the crisis of the Asian economies. The falling industrial production dragged the freight market downwards. This lasted until 2000, when the 'Asian crisis' ended and the industrial production got back on track. The improved economic fundamentals led to a long anticipated rebound of the freight market, even though it proved short-lived.

The most notable surge of the freight market took effect between 2003 and 2007, when the rates reached historical highs. The spurring growth of China and its associated imports of raw materials was the main driver behind this market rally. This ceased in the second half of 2007, when a deep financial crisis spread to the world economy and ultimately to the shipping market, causing an unprecedented plunge of freight rates in the second half of 2008.

The relationship between the state of the economy and the seaborne trade has been documented numerous times in the maritime literature. Isserlis (1938) highlights the linkage between economic cycles and freight rate movements, noting that the demand

for shipping is primarily triggered by the world economy. Platou (1970) pinpoints the influential role of the economic environment in the dry cargo market. Specifically, the sharp decline in the industrial production of 1958 reflected the sluggish world economy of that period which harmed the seaborne trade of raw materials and contributed to the falling freight rates.

Going forward, many other authors have investigated the role of macroeconomic variables in the formation of freight rates and they conclude that the major determinants of freight rates include global economic activity, industrial production growth, and oil prices (Hawdon, 1978; Strandenes, 1984; Beenstock & Vergottis, 1989; 1993).

Grammenos and Arkoulis (2002) investigate the impact of world macroeconomic factors on the stock returns of several listed shipping companies. The factors under consideration include industrial production, oil prices, inflation, exchange rates (against the USD), and laid up tonnage. The results reveal that laid up ships and oil prices have a negative effect on stock returns, whilst the exchange rate is positively related to the returns of stocks. Overall, the authors identify a strong connection between the shipping industry and the macroeconomic environment. Dikos et al. (2006) use system dynamics modelling and look into causality effects, so as to assess the macroeconomic factors that drive the tanker time charter rates. They estimate the flow of supply of tonnage through entry, exit and lay-up decisions and then they compare it with demand. Finally from their interaction they determine the key factors that affect tanker rates. In another study, Meenaksi (2009) attempts to specify the key determinants of ship investment decisions using the shipping recession of 2008 as a reference.

Alizadeh and Talley (2011a) focus on microeconomic determinants of dry bulk freight rates. They examine the effect of vessel size, age, length of lay-can, and voyage route on rates using a system of simultaneous equations. The results indicate the existence of significant relationships; therefore, those factors should be taken into considerations during chartering negotiations. In another study, Alizadeh and Talley (2011b) apply a similar methodology in the tanker market and find that the determinants of tanker rates include the ship's hull type (single or double hull), the age, the routes, the lay-can duration and the deadweight (dwt) utilization ratio (cargo / dwt).

Lee (2012) moves in a different direction and examines if the global economic conditions can have a significant effect on trade disputes. This paper bears some relevance to the subject matter of this thesis, considering that possible trade disputes may negatively influence the trading activities and reduce the demand for shipping services on certain routes. Moreover, viewing this in a smaller scale, it is likely to impede the chartering negotiations between shipowners and charterers. Tang et al. (2013) investigate the macroeconomic determinants of shipping cycles, using the market downturn of 1980s as a point of reference. In this reading, they pinpoint the following macroeconomic factors: the exchange rate of USD, the crude oil price, the inflation, and the globalization.

More recently, several authors have taken into consideration the impact of economic factors with respect to modelling and decision making in the shipping market. For example, Lyridis et al. (2014) develop forecasting models for the dry cargo market and incorporate macroeconomic variables. Batrinca and Cojanu (2014), in their attempt to specify the main drivers of the dry cargo freight market, they construct a multiple OLS

regression model and seek to detect the impact of each explanatory variable on the freight rates. The results verify the apparent negative relationship between freight rates and supply of ships, as well as the positive one between freight rates and demand. They also find that the world GDP has a positive effect on freight rates. However, the model specification needs to be checked more thoroughly, while there is no evidence that the variables fulfil the Ordinary Least Squares (OLS) assumptions. In addition, the annual data used are not able to capture the short-term fluctuations.

2. Conceptual Framework

The DBECI is divided into three major components: Power of Consumers, Liquidity and Industrial Activity. Each of them describes a separate dimension of the DBECI and their combination shapes the final composite indicator (see Figure 1). This nested structure reflects the conceptual formation of the composite indicator by the aggregation of three distinct driving forces.

Insert Figure 1 about here

The ‘Power of Consumer’ component involves the following sub-indicators: New Residential Construction (US), Euro/USD and Yuan/USD Exchange rates, and the Brent Crude Oil Price. The ‘Liquidity’ comprises the Federal funds rate and the Consumer Credit Outstanding (US), and lastly the ‘Industrial Activity’ component includes the World Industrial Production and the Manufacturing and Trade Inventories (US).

New residential construction (or Housing Starts) captures the newly issued building permits, the new construction projects and the housing that were brought to completion. The construction industry uses several dry bulk commodities such as steel, cement, clinker etc. Therefore, an increase in construction activity pushes the demand for such commodities upwards and favours the bulk carriers.

The exchange rate of Euro against the US Dollar has a significant impact on the Trans-Atlantic trade and this extends to the entire dry cargo market. In particular, a strong USD is seen as very expensive by European importers and this affects negatively the US exports of dry commodities, such as grain and coal, to Europe. Likewise, the Chinese imports from the US are significantly affected by the prevailing exchange rate. Several authors use exchange rates as explanatory variables of shipping related metrics (Goodwin and Schroeder (1991); Grammenos and Arkoulis, 2002; Tang et al, 2013).

Brent crude price tracks the prices of crude oil in the Atlantic and serves as a leading benchmark for the global oil trade. The oil price is viewed as a critical determinant of shipping freight rates by various authors (Zanettos, 1966; Beenstock and Vergottis, 1989, 1993; Grammenos and Arkoulis, 2002; Poulakidas and Joutz, 2009; Chen and Hsu, 2012; Shi et al., 2013; Tang et al., 2013; Shen and Chou, 2015). The Brent crude oil price is a major driver of the world economy. As oil prices fluctuate, inflation follows suit and ultimately determines the buying power of consumers. Crude oil is a

prime source of energy and its products have various uses that range from heating and electricity generation to their utilization as fuel in every mode of transport. Bunker fuel prices co-fluctuate with crude oil prices; therefore higher oil prices equal higher transport cost. This compels shipowners to seek higher freight rates so that they can recover the higher voyage expenses. Additionally, a possible rise in oil prices increases the production and transport costs, and eventually it is passed on the end user through higher product prices. Consequently, higher oil prices may translate into lower consumer spending and as a result into sluggish trading activity and diminished demand for raw materials.

The US federal funds rate represents a target interest rate that is set by the Federal Open Market Committee and effectively determines the interbank borrowing. When Fed decides to raise the rate, banks are discouraged from borrowing money and subsequently the loan interest rates rise, disincentivizing investments and generally reducing consumption. Some authors, such as Zanettos (1966) examine the relationship between the London Interbank Offered Rate (LIBOR) and the time charter rates. The present study employs the fed funds rate as a more representative indicator of the interest rate environment. In fact it has a longer term scope, while LIBOR is based on a questionnaire and is not fixed in advance.

The Consumer Credit report monitors the consumer credit conditions, tracking the changes in the consumer outstanding debt, as this is measured by the combination of revolving and non-revolving credit. This variable actually expresses the availability of credit for consumers and ultimately reflects their buying power.

World industrial production measures the industrial output in the global economy. This includes mining, manufacturing, electricity power, and utilities. Beenstock and Vergottis (1989, 1993) and Stopford (1999) illustrate that world industrial production is strongly related to seaborne trade. He also provides historical evidence that falling industrial production played a central role in harming the demand for ships. The level of industrial production is closely linked to the volume of seaborne trade of the underlying raw materials. Therefore, a sudden drop in industrial production can spiral the freight market downwards.

The Manufacturing and Trade Inventories and Sales (US) correspond to the aggregated value of inventories and sales across the manufacturing, retail and wholesale sectors. High inventory levels are associated with low demand for raw materials and subdued trading activity. On a larger scale, it is an indication of a slowing economy that harms the demand for raw materials and leads to the accumulation of high stockpiles. A large chunk of the aforementioned is moved by bulkers, marking the key role of inventory levels for the dry bulk market.

3. Data and Descriptive Statistics

The dataset of the current analysis involves monthly data and spans the period from January 1999 to July 2014. The selection of this interval was made in view of data availability, but it allows for a full shipping cycle.

Historical data for BCI, BPI and BSI (available from 2005 onwards) were obtained from the Clarkson's Research Services (CRLS) database.

Table 1 states the source of each item of the DBECI.

Insert Table 1 about here

Table 2 presents the Descriptive Statistics for each sub-indicator of the DBECI.

Insert Table 2 about here

The values presented in Table 2 suggest that certain variables, such as New Residential Construction, Brent Crude Oil Price, Consumer Credit Outstanding, and Manufacturing and Trade Inventories are characterized by high standard deviation, which corresponds to great volatility.

In addition, the descriptive statistics' results illustrate that most sub-indicators are negatively skewed, except Manufacturing and Trade Inventories and World Industrial Production, which are skewed to the right. According to Table 2 the sample kurtosis is less than 3 in all cases, therefore the distribution of each variable is flatter than the normal distribution.

4. Methodology

4.1 The Benefit-of-the-doubt (BOD) approach for aggregating and weighting sub-indicators.

For the construction of composite indicators (CIs), several different aggregating-weighting techniques have been employed (Melyn and Moesen, 1991; OECD, 2008). Among them, the 'Benefit of the doubt' (BOD) (Cherchye et al., 2007) is an alternative procedure, based on the Data Envelopment Analysis (DEA) (Cooper et al., 2011). BOD has been proposed for many CI cases, as a tool to compare and rank variables in terms of their performance. On this line of research, some indicative examples include the Human Development Index (HDI) (Lozano and Guitierrez ,2008; Despotis, 2005), the Technology Achievement Index (TAI) (Cherchye et al., 2008) and the Digital Access Index (Gaaloul and Khalfallah, 2013).

BOD employs linear programming to endogenously decide on the relative contribution of the sub-indicators by selecting the values of the weights assigned to each of them. This method has mainly been applied for benchmarking countries. The BOD assessment retrieves the best performing variables so as to form a benchmarking frontier, which is then used by the other variables of the model in order to estimate their maximum relative score. The formulation of the BOD model is as follows:

Given a set of m observations, a CI can be used to compare the performance of each individual observation relative to the others. The values of the CI derive from the aggregation of n individual sub-indicators (X_1, X_2, \dots, X_n), which are selected as the principal key factors. All sub-indicators are assumed to have positive contribution to the CI and. The CI for a given variable c is estimated as the weighted sum $CI_c = \sum_{i=1}^n w_i x_{ic}$

. The x_{ic} denotes the performance of observation c ($c=1, \dots, m$) in the indicator X_i and w_i the weight assigned to that indicator. Model (1) is the BOD equivalent (OECD 2008, p. 93) for the estimation of the maximum possible value of the composite index for a given observation, c_0 .

$$\begin{aligned}
 \text{Max } CI_{c_0} &= \sum_{i=1}^n w_i x_{ic_0} \\
 CI_c &= \sum_{i=1}^n w_i x_{ic} \leq 1, \quad c = 1, \dots, m \\
 w_i &\geq \varepsilon, \quad i = 1, \dots, n
 \end{aligned}
 \tag{1}$$

Model (1) is solved m times, one for each observation and estimates the values of the weights w_i , in the optimal way, so that the composite indicator's values is maximized. The second constraint bounds the values CI_c for all countries with the absolute limit 1, while the third constraint ($w_i \geq \varepsilon, i = 1, \dots, n$) ensures that the weights will take non-trivial values, larger than the positive constant ε . The BOD model (1) is often enriched with additional weight constraints to prioritize the significance of the sub-indications.

4.2 Benefit-of-the-doubt (BOD) adapted for the leading CIs.

Leading indicators are employed to predict future financial or economic trends. Unlike typical CIs which compare a fixed, predetermined set of variables, leading indicators are based on time series observations (months, years etc.) that continuously expand to future periods. When considering the BOD model for the case of leading indicators, it becomes clear that any new observation entering the system may be a potential best performer and will consequently change the efficient frontier. Thus, due to the relative assessment, the value of the CI for the rest of the observations may change over time thereby making the comparison impossible. To overcome this drawback, we propose an extension of the BOD model, which is based on the insertion of an 'IDEAL' virtual observation, which is essentially a hypothetical observation having the best possible performance. This virtual observation will dominate all existing and future units, acting as the absolute benchmark for all time periods; thus it will make the assessment scores unique and constant over time. This issue is demonstrated in the following simple example presented in Figure 2.

Insert Figure 2 about here

Five units 1,2,3,4, and 5 that correspond to certain time instances are compared along two sub-indicators X_1 and X_2 . According to the typical BOD assessment, units 5, 1, and 3 are the best performers, forming the frontier indicated by the straight line that connects them. Any other unit - except the best performing units -, is compared with its benchmark on the frontier. For example, unit 2, which is below the frontier, has a corresponding benchmark unit A' and its score derives from the ratio OA/OA' . When the IDEAL unit enters the data set, the best performing frontier degenerates to a single point and this unit undeniably becomes the unique best performer in the data set. In such a case, the benchmark of unit 2 becomes unit A'' and the corresponding score is now OA/OA'' which is obviously lower than the previous score OA/OA' . Moreover, the IDEAL unit affects the best performers on the frontier as well. Unit 5, which used to be a top performer, loses this property when compared to the IDEAL and its score is now estimated by the ratio OB/OB' .

The idea of establishing an ideal unit in DEA has been used in past research papers to rank the efficient units (Wang and Luo, 2006) and to extract a common set of weights

(Payan et al., 2014). As opposed to these approaches that define the ideal unit as the one that contains the maximum indicator values taken from the existing set of units, according to our approach the IDEAL unit transcends any existing or possible future observation, being the theoretical maximum value.

In the case of leading indicators the value of CI has to be estimated for m distinct time observations t_1, \dots, t_m . Model 1 is adjusted to include the IDEAL observation and this derives Model 2 which takes the following form:

$$\text{Max } CI_{t_0} = \sum_{i=1}^n w_i x_{it_0} \quad (2.1)$$

$$CI_t = \sum_{i=1}^n w_i x_{it} \leq 100, \quad t = 1, \dots, m \quad (2.2)$$

$$CI_{ideal} = \sum_{i=1}^n w_i x_{iideal} \leq 100 \quad (2.3)$$

$$w_i \geq \varepsilon, \quad i = 1, \dots, n \quad (2.4)$$

The x_{it} and x_{iideal} represent the values of indicator i at time t and of the IDEAL observation respectively. The objective function (2.1) maximizes the CI value for a given time t_0 . In the constraint (2.2), without loss of generality, the upper bound 1 is replaced by 100 for purposes of better presentation.

The inclusion of the IDEAL observation in model (2) rectifies the previously mentioned drawbacks and generates the following properties, which significantly enhance the model:

Property 1: Only the IDEAL can reach the maximum score of 100, i.e. $CI_{ideal} = 100$ and all other observations at time t will have score less than 100 ($CI_t < 100, \forall t$)

Property 2: The score CI_t of any past observation $t=1, \dots, m$ remains the same when a new observation $m+1$ enters the data set.

The proof of property 1 is as follows:

Since the IDEAL observation dominates all other observations in the dataset, it will automatically reach the maximum bound, that is $CI_{ideal} = 100$. Now assume that there exists another observation, say t_1 , that also achieves the highest score, i.e. $CI_{t_1} = 100$

using a specific favourite set of weights w_i^* , $i=1, \dots, n$. For the observation t_1 holds

$$CI_{t_1} = \sum_{i=1}^n w_i^* x_{it_1} = 100. \text{ With the same set of weights, the score of the IDEAL observation}$$

$$\text{should be: } CI_{ideal} = \sum_{i=1}^n w_i^* x_{iideal} > \sum_{i=1}^n w_i^* x_{t_1} = 100, \text{ since by the definition of the IDEAL,}$$

the value $\frac{x_{iideal}}{x_{i\max}}$ is greater than any other value of the indicator i in the dataset, so

$$x_{iideal} > x_{t_1} \frac{x_{i\max}}{x_{t_1}} \Rightarrow x_{iideal} > x_{t_1}. \text{ The previous inequality } \frac{CI_{ideal}}{CI_{IDEAL}} > 100 \Rightarrow CI_{ideal} > 100 \text{ contradicts}$$

the constraint (2.3) ($CI_{ideal} \leq 100$) and this leads to the conclusion that the hypothesis

that there exists a differeny observation from the IDEAL that achieves the maximum

score is false. Therefore, the IDEAL observation will be the unique best performer in

the dataset.

For the proof of Property 2 it is pointed out that since the IDEAL observation is the

unique benchmark observation in the dataset of the m time observations, it will also be,

by its definition, the unique benchmark in any future observation $m+1$, $m+2$, $m+3$ etc.

As such, it will not affect the CI score of the rest of the observations as these are only

compared to the IDEAL.

Further extending Property 2, we can conclude that for the assessment of the new time

period $m+1$, only the IDEAL observation is needed. This remark enables us to simplify

model (2) in terms of computational effort. Model (3) below, presents this simplified

form of model (2) by including only two observations; the new observation $m+1$ and

the IDEAL.

$$Max \quad CI_{t_{m+1}} = \sum_{i=1}^n w_i x_{it_{m+1}} \quad (3.1)$$

$$CI_{t_{m+1}} = \sum_{i=1}^n w_i x_{it_{m+1}} \leq 100 \quad (3.2)$$

$$CI_{ideal} = \sum_{i=1}^n w_i x_{iideal} \leq 100 \quad (3.3)$$

$$w_i \geq \varepsilon, i = 1, \dots, n \quad (3.4)$$

Model (3) can be used for the assessment of any future observation.

5. Implementation

The extended BOD model, as described in the previous sections, is applied in the case of the new, candidate index DBCECI. DBCECI is composed of eight sub-indicators presented in Table 1. Model (2) has been used to aggregate and weight these sub-indicators. In this process, two additional arrangements have been made. First, in order to prioritize the contribution of the World Industrial Production and New Residential Construction sub-indicators to the values of the DBCECI index, the additional constraints: $w_1, w_8 \geq w_2, w_3, w_4, w_5, w_6, w_7$ have been set to model (2). This is due to the fact that these two variables have a stronger theoretical connection to seaborne trade compared to the other sub-indicators. Second, following the lines of the BOD method, the values x_{ij} are normalized using the max-min rescaling formula $\bar{x}_{ij} = \frac{x_{ij} - x_{i\min}}{x_{i\max} - x_{i\min}}$, where $x_{i\min}$, $x_{i\max}$ are the lowest and highest bounds respectively (see Table 2) and correspond to the ideal point, while \bar{x}_{ij} are the new normalized values. Given that the values \bar{x}_{ij} fall inside the interval [0..1], the ideal point is set to 1, i.e. $x_{ideal} = 1$. In this respect, model (2) is run using the normalized values \bar{x}_{ij} , rather than raw data.

Insert Table 3 about here

Figure 3 presents the fluctuations of DBECI from January 1999 to July 2014. It is worth noting that the sharp drop of DBECI before 2007 demonstrates that this leading indicator would have been able to predict the market crash of 2007 and the subsequent shipping market recession.

Insert Figure 3 about here

6. Validation

The next step is the exploration of potential linkages between the DBECI and the dry cargo freight market. Considering that this relationship gives impetus to the creation of this composite indicator in the first place, the establishment of a significant causal relationship between DBECI and freight rates will essentially validate the role of DBECI as a leading indicator.

Hence, the robustness of this candidate indicator is assessed by means of causality analysis. In particular, we employ the three Baltic Exchange indices, i.e. the Baltic Capesize Index (BCI), the Baltic Panamax Index (BPI) and the Baltic Supramax Index (BSI), as representative indicators of the freight rate fluctuations in the dry bulk market for three different vessel sizes.

The analysis begins with testing for unit roots using two widespread stationarity tests: the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test and the Augmented Dickey–Fuller (ADF) test. Both tests are carried out in the log-levels and log-differences of the series of this analysis. The KPSS test examines the null hypothesis of stationarity under two different assumptions: First the series have an intercept, and second, a constant and linear trend. On the other hand, the ADF test is performed on the log- levels and log-differences of the same variables and tests the null hypothesis of non-stationarity under three different assumptions: An intercept, a constant and linear trend, and neither.

If the series are found non-stationary it is necessary to examine the existence of co-integration, using the Johansen test. Then, a VAR model is developed for the levels of the data, with the appropriate lags being determined using various lag length criteria, such as the sequential modified LR test statistic (LR), the Final prediction error (FPE), the Hannan-Quinn information criterion (HQ), the Schwarz information criterion (SC) and the Akaike information criterion (AIC) (See Appendix). Thereafter, it is checked if the model is well specified by looking at its R-squared, and by applying the VAR Residual Serial Correlation LM test and the VAR Residual Heteroskedasticity Test.

Based on that model, the study runs Granger causality tests, as a way to investigate the existence of causal relationships. When the results are significant, it is sensible to proceed to Impulse Response (IR) analysis in order to explore the manner in which the variables affect each other. In particular, IR analysis will indicate if changes in one variable have a positive or negative effect on the other and how long this effect will last. It should be noted that if two variables are co-integrated, the IR analysis should be based on a VECM model and if not, on an unrestricted VAR.

6.1 Stationarity Tests

The ADF and KPSS unit root tests are carried out in the log-levels and log-differences of DBECI and Baltic indices. The KPSS tests the null hypothesis of stationarity under two different assumptions: First the series have an intercept, and second, a constant and linear trend. Alongside, the ADF test is performed on the log- levels and log-differences of the same variables and tests the null hypothesis of non-stationarity under three different assumptions: An intercept, a constant and linear trend, and neither.

Insert Table 4 about here

Insert Table 5 about here

The results of the ADF and KPSS tests are presented in Tables 4 and 5. The combination of those two tests provides sufficient evidence that all series are non-stationary in level forms, but stationary in first differences.

6.2 Co-integration Analysis

Given that the series are integrated of order 1, Johansen Co-integration test investigates the existence of co-integrating relations. The results are presented in Table 6:

Insert Table 6 about here

The results demonstrate that there are no co-integrating relations. Therefore each pair of variables will be modelled using an unrestricted VAR.

6.3 Causality Analysis

Insert Table 7 about here

Table 7 reports the outcome of several Granger causality tests between the BDECI and the respective Baltic Exchange indices. It turns out that there is significant unidirectional causality between the BDECI and each of the representative indices. Specifically, BDECI causes BCI, BPI and BSI at a 1% level. On the flip side, there is no causality running from any of those indices to BDECI. Therefore, this is an indication that BDECI could be used as an exogenous variable in a freight forecasting model.

In addition, the LM tests demonstrate that the models are free from serial correlation, with the exception of the BCI – DBECI VAR model, which appears auto-correlated at a high level though (10%).

Finally, even though the variables were converted into logarithmic forms, residual heteroscedasticity is still present as shown by the relevant White heteroscedasticity tests (no-cross terms). This may be due to the uneven distribution of the variables of this analysis, as indicated by the skewness that the descriptive statistics of Table 1 detect. Another possible source of heteroscedasticity is the existence of outliers, combined with the small sample size.

In any case, although the presence of heteroscedasticity harms the efficiency of estimators, it does not affect their consistency and unbiasedness. Hence, normally this is not a reason to reject an otherwise satisfactory model.

6.4 Impulse Response Analysis

The next step involves IR analysis. The figures below depict the responsiveness of the freight market to a positive shock to DBECI. Specifically, IR analysis detects the precise reaction of each Baltic index, given a sudden spike in the DBECI.

The vertical axis measures the magnitude of the effect of the shock on each variable and the horizontal axis the number of months after the shock.

Insert Figure 4 about here

According to Figure 4 the BCI is expected to head upwards over the short and medium term, suggesting that a booming economic environment has a long lasting positive impact on Capesize rates. Eventually, after some fluctuations the effect of the shock dies out.

This behaviour is consistent with the theoretical expectations of the relationship under consideration. Therefore, IR analysis provides empirical evidence of the direction of the relationship between DBECI and BCI and effectively validates the utilization of the DBECI as a leading indicator of the freight rates.

Insert Figure 5 about here

Figure 5 shows the reaction of BPI to a positive shock to DBECI. The exhibit demonstrates that the response of the BPI is quite similar to BCI. The main difference is that in the case of Panamax vessels the full effect of the shock comes up slower, while it dies out a little sooner and slightly more steeply. Therefore, Capesize ships are more susceptible to changes in economic conditions, than the smaller and relatively more versatile Panamax vessels.

Insert Figure 6 about here

Finally, Figure 6 shows that BSI responds in a similar manner as the other two types of bulk carriers. However, given that the BSI has been found co-integrated with the DBECI, the effect of the shock does not die out. On the contrary, the two variables reach a long-term equilibrium emanating from their co-integrating relation.

7. Conclusions

The construction of the DBECI intends to summarize several dimensions of the economic environment that surrounds the dry cargo market. Within this framework, the proposed indicator aims to synthesize various economic factors and capture their aggregate influence on the dry market. Specifically, the DBECI encompasses three

distinct sub-groups of variables, with each of them reflecting a separate dimension of the impact of the economic environment on the freight market.

The aggregation of different individual indicators into a common composite indicator requires sound theoretical and quantitative analysis. Thus, the first step involves the development of the theoretical framework, which dictates the selection process of the underlying variables and explains their relevance to the dry bulk freight market. Following the identification of the most representative macroeconomic variables, the present study adopts a modification of a linear programming method (the 'Benefit of the Doubt approach'), with the purpose of assigning appropriate weights to each sub-indicator and synthesizing them. This enhances the credibility of the proposed index and allows its linkage with the dry bulk freight market. The latter is confirmed through a series of pertinent statistical tests. In particular, the empirical analysis provides evidence that there is significant causality between the DBECI and each of the Baltic Exchange indices under consideration. In addition, the Impulse Response analysis indicates that the DBECI has a positive short-term effect on freight rates.

Overall, it turns out that the construction of a new composite index tailored to the dry bulk freight market sheds some light on the relationship between the freight market and its economic environment, and opens new avenues for research.

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Tables

Indicator	Data Source
x_1 New Residential Construction (US)	<i>U.S. Census Bureau</i>
x_2 Exchange Rate Euro/USD	<i>Eurostat</i>
x_3 Exchange Rate Yuan/USD	<i>Global Economic Monitor (GEM)</i> <i>(World Bank Group)</i>
x_4 Brent Crude Oil Price	<i>Clarkson Shipping Intelligence Network</i>
x_5 Federal Funds Rate	<i>Board of Governors of the Federal Reserve System</i>
x_6 Consumer Credit Outstanding (Levels) (US)	<i>Board of Governors of the Federal Reserve System</i>
x_7 Manufacturing and Trade Inventories (US)	<i>U.S. Census Bureau</i>
x_8 World Industrial Production	<i>Global Economic Monitor (GEM)</i> <i>(World Bank Group)</i>

Table 1: The eight sub-indicators of the DBECI index

<i>Sub-Indicators</i>								
<i>Statistic</i>	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8
Mean	1355.04	1.22	7.48	63.36	2.25	2336883.82	1028734.88	1337.01
Median	1552	1.28	7.90	59.16	1.73	2434197.59	1022219.00	1340.00
Variance	295424.59	0.03	0.71	1221.50	4.72	2.18E+11	3.39E+10	29132.92
Std. Deviation	543.53	0.18	0.84	34.95	2.17	467178.32	184228.75	170.68
Minimum	513	0.85	6.05	10.25	0.07	1431200.00	674466.00	1020.00
Maximum	2263	1.58	8.28	137.19	6.54	3233200.00	1400400.00	1710.00
Interquartile Range	931	0.28	1.54	72.47	4.47	701606.50	328271.00	300.00
Skewness	-0.11	-	-	0.28	0.54	-0.22	0.19	0.06
Kurtosis	-1.41	-	-	-1.32	-	-0.88	-1.14	-1.16

Table 2: Descriptive statistics

	$x_{i\min}$	$x_{i\max}$
x_1 New Residential Construction (US)	200	3000
x_2 Exchange Rate Euro/USD	0.5	2
x_3 Exchange Rate Yuan/USD	2	15
x_4 Brent Crude Oil Price	5	210
x_5 Federal Funds Rate	0.01	10
x_6 Consumer Credit Outstanding (Levels) (US)	950000	4200000
x_7 Manufacturing and Trade Inventories (US)	500000	1750000
x_8 World Industrial Production	900	2700

Table 3: Lower and Upper bounds used for max-min rescaling.

	Log-Levels			Log-first differences		
	Intercept	Const. trend	& None	Intercept	Const. trend	& None
DBECI	-2.338886	-2.395470	-0.836106	-2.710362*	-2.704792	-2.658569***
BCI	-2.620608*	-2.517031	-0.113657	-10.15873***	-10.19775***	-10.18645***
BPI	-2.525228	-2.497892	-0.304766	-10.84987***	-10.89695***	-10.87895***
BSI	-2.142959	-3.442606*	-0.467363	-7.410905***	-7.415576***	-7.437151***

Notes:
*** indicates rejection of the null at 1% level, **at 5% and * at 10%
H₀: the series is non stationary, H₁: the series is stationary

Table 4: ADF test (DBECI)

	Log-Levels		Log-first differences	
	Intercept	Const. & trend	Intercept	Const. & trend
DBECI	0.228546	0.167210**	0.113229	0.094181
BCI	0.354190*	0.328912***	0.152610	0.035532
BPI	0.331683	0.331278***	0.167447	0.023463
BSI	0.770942***	0.094768	0.073853	0.041639

Notes:
*** denotes rejection of H₀ at 1% level, **at 5% and * at 10%
H₀: the series is stationary, H₁: the series is non stationary
The bandwidth for each test is chosen on the basis of the Newey-West selection using Berlett kernel

Table 5: KPSS test (DBECI)

Pair of variables	Lags	Hypothesized No. of CE(s)	Trace	0.05 CV (trace)	Max Eigenvalue	0.05 CV (Max Eigen.)
BCI - DBECI	8	None	10.16576	20.26184	6.904804	15.8921
BPI - DBECI	8	None	11.94067	20.26184	9.306167	15.8921
BSI - DBECI	5	None*	17.73629	20.26184	16.53512	15.8921
		At most 1	1.201178	9.164546	1.201178	9.164546

Notes:

* denotes rejection of the hypothesis at the 0.05 level.

The tests assume a restricted intercept in the co-integrating equation and no deterministic trends in the series.

The trace statistic tests $H_0: r$ cointegrating relations against $H_1: k$ cointegrating relations.

The max eigenvalue statistic tests $H_0: r$ cointegrating relations against $H_1: r+1$ cointegrating relations.

Table 6: Johansen Co-integration test (DBECI)

Dependent variable	Excluded variable	Model	Lags	Chi-sq. (p-value)	Outcome	Residual Serial Corr. LM test	Residual Heteroskedasticity	R-sq.
BCI	DBECI	VAR	8	0.0074	causality at 1%	0.0755*	0.0084***	0.298954
			8	0.5710	No causality			
BPI	DBECI	VAR	8	0.0002	causality at 1%	0.4741	0.0001***	0.219027
			8	0.6256	No causality			
BSI	DBECI	VECM	5	0.0014	causality at 1%	0.7917	0.0000***	0.343648
			5	0.2633	No causality			

Notes:

*** indicates rejection of H_0 at 1% level, **at 5% and * at 10%

H_0 : All lagged terms of excluded variable insignificant

The test statistic follows the chi-square distribution under H_0

VAR/VEC Residual Heteroskedasticity Tests: No Cross Terms / H_0 : homoscedasticity in residuals

VAR/VEC Residual Serial Correlation LM test / H_0 : no serial correlation at lag order h

Table 7: Granger Causality Test (DBECI)

Figures

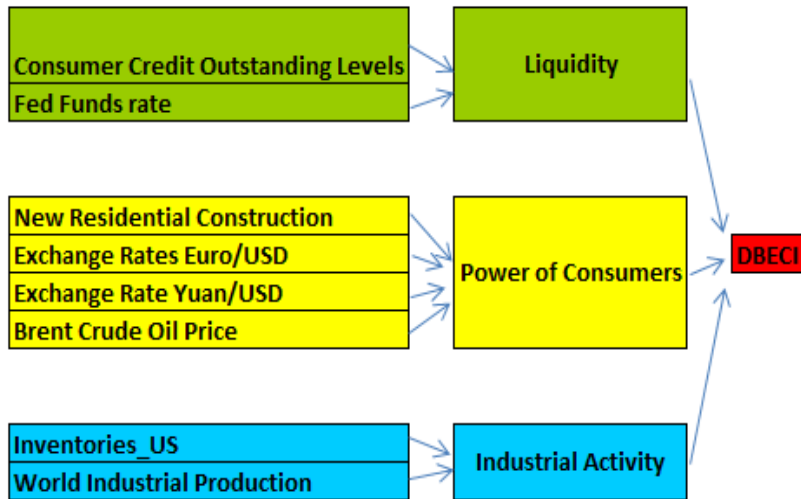


Figure 1: DBECI structure

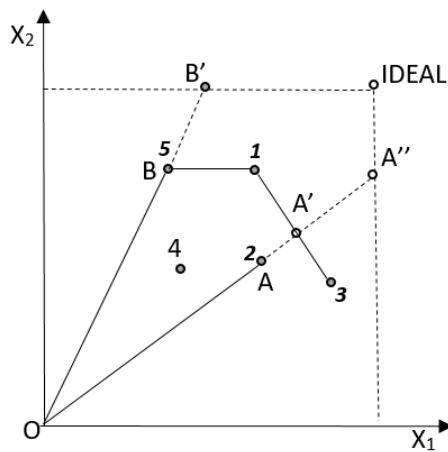


Figure 2: Simple example with two sub-indicators

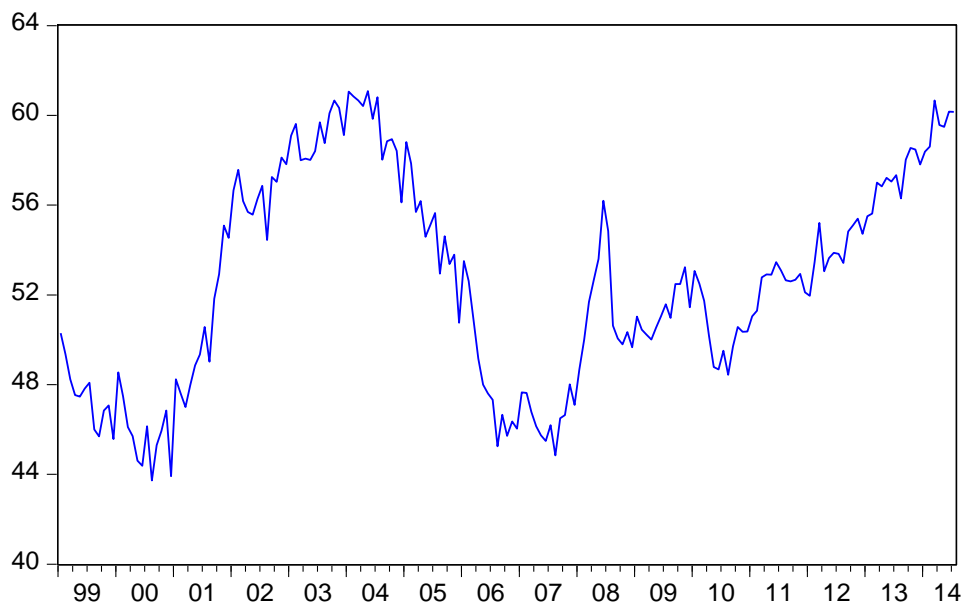


Figure 3: DBECI

Response of DBCI to DDBECI

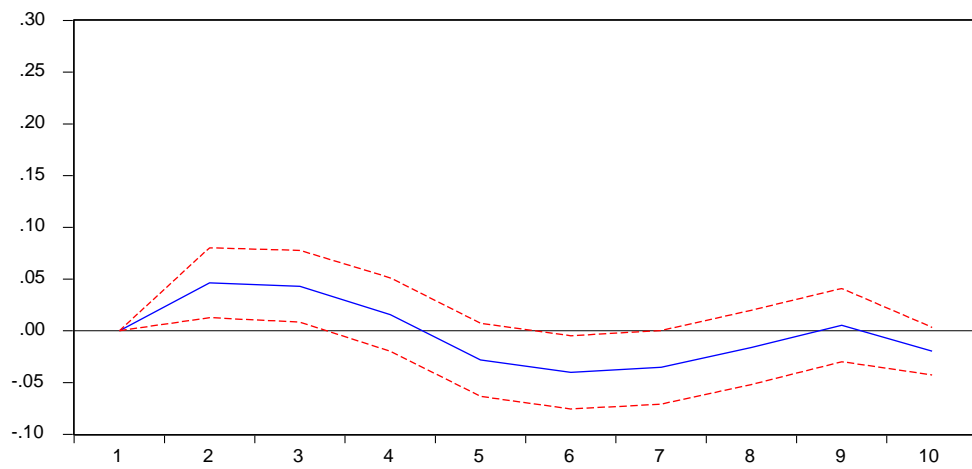


Figure 4: BCI and DBECI

Response of DBPI to DDBECI

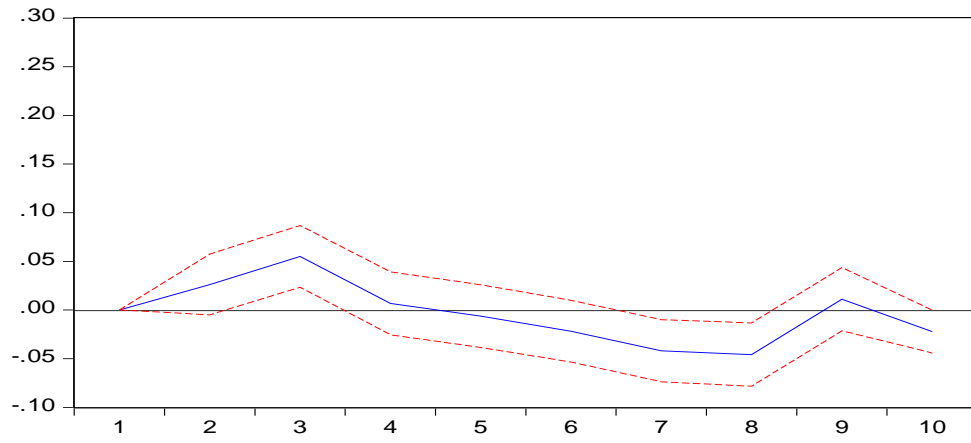


Figure 5: BPI and DBECI

Response of BSI to DBECI

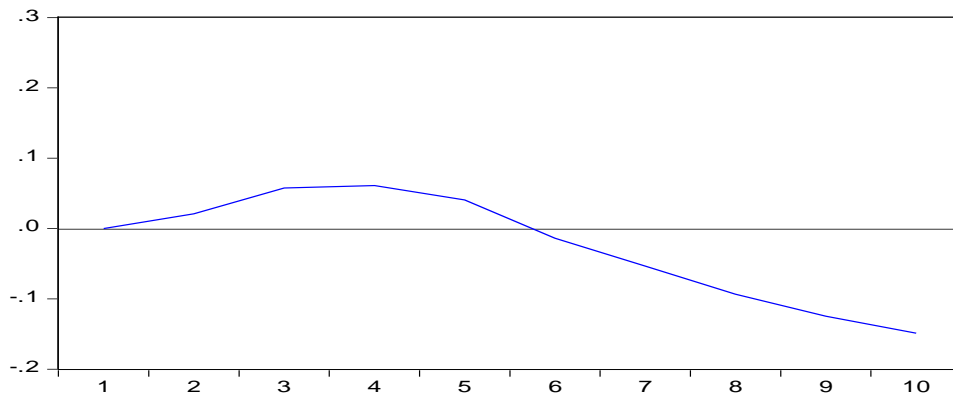


Figure 6: BSI and DBECI