ANALYSIS OF THE INTERACTION BETWEEN CAPESIZE AND PANAMAX FREIGHT MARKETS

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ABSTRACT

Without the dry bulk shipping market, world trade, industry and our current lifestyles could not be maintained. The dry bulk market is very dynamic due to interactions of its various components. The purpose of this study is to analyze the linkages between the Capesize market segment and the Panamax market segment in order to understand the price mechanism and the behavior of market participants.

Keywords: *Capesize, Panamax, VAR models, dry bulk shipping*

1. INTRODUCTION

In 2012, more than one-third of all international seaborne trade consisted of dry bulk cargo. The importance of the dry bulk shipping market is that without her, world trade, industry and our current lifestyles could not be maintained. Dry bulk shipping market is segmented by ship size and the main types of bulk carriers include Handies, Panamax and Capesize.

Panamax are the mid-sized cargo ships that are capable of passing through the lock chambers of the Panama Canal which are 320.04 m in length, 33.53 m in width, and 12.56 m in depth. These limits have influenced the ship building companies to build Panamax vessels strictly in accordance with the dimensions (width, length and depth) of the lock chambers and the height of the Bridge of the Americas. A Panamax shouldn't exceed the dimensional limit of 294.13 m in length, 32.31 m in width and 12.04 m draught wise in order to easily and safely fit to the lock chambers and the height of the Bridge of Americas at Balboa. Panamax ships are in operation since the opening of the Panama Canal in 1914. In dry bulk shipping, Panamax vessels are classified as ships with a cargo-carrying capablility between 60 000 and 100 000 dwt. They mainly carry coal, grain and, to a lesser extent, minor bulks, including steel products, forest products and fertilizers. They operate in the Caribbean and Latin American regions.

Capesize are large-sized bulk carriers and tankers typically above 150 000 dwt. Capesize vessels are too large in size (especially their draught) to pass through the Panama Canal. As a result, they must transit via Cape Horn to travel between the Atlantic and Pacific oceans. Earlier, they were not fit to pass through the Suez Canal and required to take a long root via the Cape of Good Hope to travel between the Indian and Atlantic Oceans. But the deepening of the Suez Canal from 18 m to 20 m in 2009 permits most Capesize vessels to pass through it. Due to their large dimensions and deep draughts, Capesize ships are suitable to serve only large ports with deep water terminals in the world. As a result, they can serve a comparatively small number of ports in the world. Capesize ships are commonly used in transportation of coal, iron ore and commodity raw materials. Because of this fact, they are often termed as bulk carriers rather than tankers. In the subcategory of Capesize vessels are included the very large ore carriers (VLOC) and very large bulk carriers (VLBC) of above 200 000 dwt. These vessels are mainly designed to carry iron ore. According to estimates, 93% cargo of Capesize bulkers comprises of iron ore and coal. There is a huge demand for large Capesize vessels in the world today. While a standard Capesize vessel is around 175 000 dwt, bulkers up to 400 000 dwt or even more have been built in recent times to meet the growing demand for bulk ore transportation carriers. But with few of world's ports having infrastructure to handle ships larger than 200 000 dwt, port access has emerged as a major problem for Capesize vessels. At present, most of large Capesize bulkers are being used for ore transportation between Australia and China, and Brazil and China.

The dry bulk market is very dynamic due to interactions of its various components. When freight rates for Capesize ships are high, charterers prefer to carry goods by two Panamax ships instead. As the number of these options increases, the freight rates for Capesize ships fall. Reversely, when freight rates for Panamax ships are high, there are few goods that can be loaded on Capesize ships, because Panamax ships carry, in addition to ore and coal, grains and fertilizers that can rarely be transported by Capesize ships.

2. LITERATURE REVIEW

The existing researches on the use of vector – autoregressive (VAR) models in shipping industry are scarce.

Bulut et al. (2012) perform an empirical analysis for the prediction of the chartering rates of a group of dry bulk cargo ships. They extend a fuzzy integrated logical forecasting method for multivariate systems by using a vector autoregressive model. The results are compared by the root mean squared error metric. In addition, the C-means clustering method is proposed to optimize the distributions of the cluster sets and the half of the standard deviation is implemented for the initial intervals of the C-means clustering[1].

Chou (2011) investigates the relationships between the global oil index and one year forward freight agreements by applying a vector autoregressive moving-average model in order to provide guidance for entering and exiting bulk shipping markets. The author demonstrates the existence of a stage one lag effect between Capesize forward freight agreements and the global oil index. The final results highlight that an economically meaningful structure exists in a set of bunker world indices and that there are stable long-run relationships between the two variables[2].

The freight rate as a price reflects vital information regarding ship supply and cargo transportation demand. Therefore, it becomes imperious to understand its dynamic properties. Ko (2013) analyzes the term structure in dry bulk freight market by applying a VAR model and two time-varying coefficient models on monthly data set from 1992 to 2012. According to the results of research, the response of long-term rate to short-term structural shock is small and statistically insignificant, while the response of short-term rate to long-term structural shock is large and statistically significant. Furthermore, overall, there is lack of evidence for the stable adjustment speed in both equations for the short and long-term freight rate[3].

The exports of a country are crucial for a country's overall growth. Nadeesha and De Silva (2013) examine the development of Sri Lanka exports, trying to highlight a relationship between exports and shipping services. By applying a Vector auto-regressive analysis, the authors try to produce a proper forecasting model for shipping demand using export in the country. According to the results, there is a strong straight line relationship between the value of exports and the amount of cargo loaded[4].

Xu et al. (2008) investigate the dynamic interrelationships between the sea freight and shipbuilding markets by applying a vector error correction model. Many practitioners argue that the freight rates rely on the shipbuilding activities, while other specialists argue that demand for shipbuilding is activated by the demand of freight market. The findings show that there exists a co-integration relationship between freight rate and shipbuilding price, such that the two rates are related to form an equilibrium relationship in the long run. Concluding, the shipbuilding prices are a function of the past history of freight rate, rather than the expected future values of freight rate[5].

3. DATA AND METHODOLOGY

This research applies a vector autoregressive model in order to analyze the linkages between two important components of the dry bulk shipping market, namely the Capesize market segment and the Panamax market segment. The daily data series of Baltic Capesize Index and Baltic Panamax Index for the time interval 1.03.1999 – 23.10.2013 were used for the empirical study. Data were collected from Baltic Exchange database and the analysis was performed with EViews 7.

A VAR model can be defined as a set of linear dynamic equations where each variable is specified as a function of an equal number of lags of itself and all other variables in the system. The VAR model used in this research paper has the following hypothesis:

$H_1 : BCI = f(BPI)$

$H_2 : BPI = f(BCI)$

The VAR model allows symmetric treatment of the two variables considered. Therefore, it comprises two equations:

$$BCI_t = \alpha_1 + \sum_{j=1}^{k} \beta_j \ x\ BCI_{t-j} + \sum_{j=1}^{k} \chi_j \ x\ BPI_{t-j} + \varepsilon_{1t}$$

$$BPI_t = \alpha_2 + \sum_{j=1}^{k} \delta_j \ x\ BPI_{t-j} + \sum_{j=1}^{k} \phi_j \ x\ BCI_{t-j} + \varepsilon_{2t}$$

where α_1, α_2 are the intercept terms, $\beta, \chi, \delta, \phi$ are the coefficients of the endogen variables and the ε are the stochastic error terms.

4. EMPIRICAL ANALYSIS

Firstly, the ADF test (Augmented Dickey-Fuller) was applied in order to verify the stationarity of time series. A time series is said to be stationary if its mean, variance and its covariances remain constant over time. From an economic point of view, shocks to a stationary time series are temporary and, over time, the effects of the shocks will dissipate. According to Table 1, the existence of a unit root was estimated for the original data and the absence of a unit root for the first-difference data. If the probability is higher than the significance level of 1% the variable is non-stationary. Therefore, the variables are integrated of order 1.

Table 1. The ADF test

BCI		**BPI**	
l(0)	l(1)	l(0)	l(1)
H0: The time series has a unit root (non-stationary)			
0.1063	0.0000	0.2004	0.0000

Source: own estimations

In order to verify if the past values of a variable X_1 contain information that helps predict a variable X_2 above and beyond the information contained in past values of X_2 alone, the Pairwise Granger causality test was applied (Table 2). If the probability is higher than the significance level of 1%, the null hypothesis is accepted. Otherwise, the null hypothesis is rejected.

Table 2. Pairwise Granger causality test

Null hypothesis	**Probabilities**
D_BPI does not Granger Cause D_BCI	7.E-12
D_BCI does not Granger Cause D_BPI	5.E-34

Source: own estimations

Taking in consideration that first difference data became stationary and the Pairwise Granger test reflects causality linkages between variables, a VAR model with 2 variables was created. A VAR model is valid if it has an optimal number of lags, if it's stable and if its residuals have normal distribution, homoskedasticity and lack of autocorrelation.

The number of lags of a VAR model must capture the system dynamics without consuming too many degrees of freedom[6]. In order to determine the optimal number of lags, the criteria provided by LR Sequential tests**,** Akaike Criterion**,** Schwarz and Hanna-Quinn Criterion tests were used. According to Table 3, the VAR model has 4 lags.

Table 3. Estimation of the optimal number of lags

LR	**FPE**	**AIC**	**SC**	**HQ**	**Chosen lag**
4	4	4	4	4	4

Source: own estimations

The stability of the estimated VAR model was tested with "AR Roots Table" test which indicates that all roots are subunitary and the model is stable (Table 4).

Table 4. VAR model stability

<table>
<tr><th>Results</th><th colspan="2">Roots modulus</th></tr>
<tr><td rowspan="4">No root lies outside the unit circle.
VAR satisfies the stability condition.</td><td>0.744890</td><td>0.744890</td></tr>
<tr><td>0.552036</td><td>0.552036</td></tr>
<tr><td>0.537325</td><td>0.370897</td></tr>
<tr><td>0.338825</td><td>0.338825</td></tr>
</table>

Source: own estimations

Regarding the quality of residuals, their normal distribution, homoskedasticity and lack of autocorrelation were tested (Table 5). If the probability is higher than the significance level of 1%, the null hypothesis is accepted. Otherwise, the null hypothesis is rejected.

Table 5. Residuals tests

<table>
<tr><th colspan="4">Autocorrelation LM test</th></tr>
<tr><td colspan="4">H0
No serial correlation at lag order h</td></tr>
<tr><td>Lag 1:
0.42</td><td>Lag 2:
0.24</td><td>Lag 3:
0.221</td><td>Lag 4:
0.315</td></tr>
<tr><td colspan="4">Cholesky (Lutkepohl) Normality test</td></tr>
<tr><td colspan="4">H0
Residuals are multivariate normal</td></tr>
<tr><td>Skewness</td><td colspan="2">Kurtosis</td><td>Jarque-Bera</td></tr>
<tr><td>0.2981</td><td colspan="2">0.1555</td><td>0.1558</td></tr>
<tr><td colspan="4">White Heteroskedasticity test</td></tr>
<tr><td colspan="4">H0
no heteroskedasticity</td></tr>
<tr><td colspan="4">0.1456</td></tr>
</table>

Source: own estimations

Since all the validity conditions are met, the VAR model can be defined as follows:

$$BCI_t = \alpha_1 + \beta \text{ x } BCI_{t-4} + \chi \text{ x } BPI_{t-4} + \varepsilon_{1t}$$
$$BPI_t = \alpha_2 + \delta \text{ x } BPI_{t-4} + \phi \text{ x } BCI_{t-4} + \varepsilon_{2t}$$

Table 6. VAR model estimation

	D_BCI	D_BPI
D_BCI(-1)	0.882495	0.084718
	(0.01756)	(0.00670)
	[50.2598]	[12.6533]
D_BCI(-2)	-0.250934	-0.078887
	(0.02280)	(0.00870)
	[-11.0043]	[-9.07255]
D_BCI(-3)	-0.073655	0.034458
	(0.02295)	(0.00875)
	[-3.20962]	[3.93795]
D_BCI(-4)	0.059341	-0.010557
	(0.01783)	(0.00680)
	[3.32842]	[-1.55292]
D_BPI(-1)	0.349860	1.105005
	(0.04597)	(0.01753)
	[7.61118]	[63.0438]
D_BPI(-2)	-0.391910	-0.374179
	(0.06715)	(0.02561)
	[-5.83598]	[-14.6126]
D_BPI(-3)	0.097531	0.045211
	(0.06684)	(0.02549)
	[1.45921]	[1.77396]
D_BPI(-4)	0.041647	-0.072603
	(0.04426)	(0.01688)
	[0.94099]	[-4.30209]
C	0.152005	0.065183
	(1.54670)	(0.58977)
	[0.09828]	[0.11052]
R-squared	0.564614	0.757745
Adj. R-squared	0.563660	0.757214
Sum sq. resids	31965868	4647775.
S.E. equation	93.57015	35.67932
F-statistic	591.8324	1427.485
Log likelihood	-21800.49	-18271.74
Akaike AIC	11.91776	9.989476
Schwarz SC	11.93301	10.00473
Mean dependent	0.529508	0.280601
S.D. dependent	141.6527	72.41102
Determinant resid covariance (dof adj.)		9820727.
Determinant resid covariance		9772488.
Log likelihood		-39840.63
Akaike information criterion		21.78067
Schwarz criterion		21.81119

Source: own estimations

The VAR model estimated above describes the autoregressive connections between the Capesize market segment and the Panamax market segment. Based on the estimated model, the impulse-response functions can be determined. The impulse-response functions show the impact of a shock of the Capesize market segment on Panamax market segment and vice-versa (Figure 1).

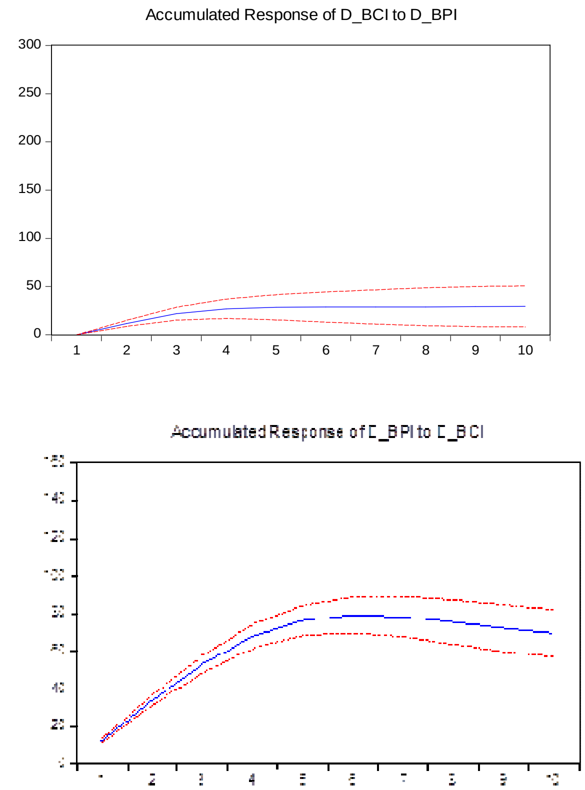

Figure 1. The impulse-response functions
Source: Own estimations

5. CONCLUSIONS

The importance of the dry bulk shipping market is that without her, world trade, industry and our current lifestyles could not be maintained. Dry bulk shipping market is segmented by ship size and the main types of bulk carriers include Handies, Panamax and Capesize. The dry bulk market is very dynamic due to interactions of its various segments.

According to Figure 1, there is a bidirectional relationship between the Capesize market segment and the Panamax market segment, but the influence of Capesize segment on Panamax segment is much stronger than the reverse one. Both market segments follow the same pattern during the analyzed time interval. The explanation of this significant difference lies in the fact that when freight rates for Capesize ships are high, charterers look at splitting their cargo lots in two and to ship them by two Panamax ships instead and in this way the freight rates for Capesize ships fall. Reversely, when freight rates for Panamax ships are high, there are few goods that can be loaded on Capesize ships, because Panamax ships carry, in addition to ore and coal, grains and fertilizers that can rarely be transported by Capesize ships.

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