AN EMPIRICAL ANALYSIS OF BIDIRECTIONAL RELATIONSHIPS BETWEEN VARIOUS COMPONENTS OF BALTIC SUPRAMAX INDEX

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ABSTRACT

In shipping, the freight market represents the adjustment mechanism linking supply and demand. Most of the times, the time charter level is a consequence of the equilibrium between demand and supply of ships in the area, but there are also situations when the market raises significantly in an area and, as a consequence, vessels situated at a shorter or a longer distance from that area are ballasting toward the hot area, shattering the equilibrium. The purpose of this study is to assess the bidirectional relationships between various components of Baltic Supramax Index by applying vector autoregressive models.

Keywords: *Baltic Supramax Index, shipping demand, shipping supply, VAR models*

1. INTRODUCTION

In the context of globalization, shipping volumes reached impressive levels. Bulk carriers represent one of the most important means of transportation of our time as they carry billions of tones of goods along major trade routes. Bulk carriers come in all sizes, from the smallest ships of only a few hundred tons deadweight to the largest of over 360 000 tons.

One very important size is the "Supramax", a type which became more and more popular since 2001. These vessels are ranging between 50 000 mt dwt and 61 000 mt dwt, have usually five cargo holds and deck cranes with a lifting capacity between 25 mt and 40 mt with most vessels being fitted with own grabs. A fairly big number are constructed as double hull vessels. Most of the bulk carriers being delivered recently are of double hull constructions and many of the sizes up to Supramax are so called "open hatch" or "semi open hatch" types, which mean they have a wide hatch opening with very narrow deck between hatch coaming and ship's side. Supramax vessels are very popular among dry cargo shippers due to their larger cargo carrying capacities and on-board cargo handling flexibility. Their favorable size allows them to trade in a much wider range of world ports and terminals. Supramax vessels are generally purposed for medium or large ports/berth that may not be able to accommodate a larger vessel due to length or draft restrictions, or those that lack transshipment infrastructure. Supramax vessels increasingly compete with Panamax ships. This is due to their growing size. In addition, they benefit from better fuel efficiency. The Supramax can call up river easier than its bigger brother the Panamax and is generally considered to be more agile, allowing access to tighter spaces. The competitiveness of Supramax vessels when compared to Panamax is also reflected in the freight rate developments.

As far as concerns the freight rate developments, Baltic Exchange produces a wide variety of shipping indices covering different vessel sizes and different cargo types. The Baltic Supramax Index (BSI) was officially launched in January 2006. The Baltic Supramax Index reflects freight rates for a 52 000 mt dwt Supramax-type vessel and consists of six trip-charter routes whose composition is broadly similar to that of the Baltic Capesize Index and Baltic Panamax Index. Routes S1A and S1B are trips from Europe (the northern Continent in the case of route S1A and the northeast Mediterranean in the case of S1B) for delivery anywhere in the region between Singapore and Japan. These routes have a combined weighting of 25% in the index. Route S2 is the trans-Pacific route reflecting movements of cargoes from Australia to Japan, South Korea or China. Route S3 represents the trip back from the Far East to Europe. Each of these routes has a weighting of 25% in the index. At last, routes S4A and S4B highlight cargo movements in the Atlantic basin: route S4A is for a trip from the US Gulf to Europe and route S4B is for a trip from Europe to the US gulf. These routes have a combined weighting of 25% in the index.

According to Alizadeh and Nomikos, the composition of the Baltic routes has to reflect current trends and developments in the freight market and its updates are decided regularly by the Baltic Exchange and its appropriate committees, which consult with the industry, market users and derivative brokers to ensure that market information remains representative of market trends[1].

Table 1. Routes of BSI on 18th October 2013

Route	S1A	S1B	S2	S3	S4A	S4B
Value	20756	17645	11165	6364	21628	6339

Source: www.balticexchange.com

According to Stopford, the freight market represents the adjustment mechanism linking supply and demand. Once the freight rate is established, shippers and shipowners adjust to it and eventually this brings supply and demand into balance. But, in practice, the demand is volatile and supply adjusts to demand with a significant time-lag, generating irregular freight cycles[2].

As can be seen from the time charter levels for each individual route of the BSI there are significant differences between regions (Table 1). Most of the times the time charter level is a consequence of the equilibrium between demand and supply of ships in the area, but there are also situations when the market raises significantly in an area and, as a consequence, vessels situated at a shorter or a longer distance from that area are ballasting toward the hot area and, in this case, they put pressure on the supply and either reduce the increase in the time charter levels from that area or reduce the time charter levels from that area. Ballasting of ships from an area to the other is also changing the equilibrium in the area they are leaving from and, in turn, the market in that area may start moving up or stop moving down.

2. LITERATURE REVIEW

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

Xu et al. (2008) analyze 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[3].

Chou (2011) examines 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[4].

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[5].

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) investigates 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[6].

The exports of a country are crucial for a country's overall growth. Nadeesha and De Silva (2013) analyze 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[7].

3. DATA AND METHODOLOGY

In this study, a vector autoregressive model was applied in order to analyze bidirectional relationships between various components of the Baltic Supramax Index. The daily data series of S1B, S3 and S4A routes for the period 02.01.2007 – 18.10.2013 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 models used in this paper have the following hypothesis:

a) $H_1 : S1B = f(S3)$
$H_2 : S3 = f(S1B)$

b) $H_1 : S1B = f(S4A)$
$H_2 : S4A = f(S1B)$

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

$$S1B_t = \alpha_1 + \sum_{j=1}^{k} \beta_j \ x \ S1B_{t-j} + \sum_{j=1}^{k} \chi_j \ x \ S3_{t-j} + \varepsilon_{1t}$$

$$S3_t = \alpha_2 + \sum_{j=1}^{k} \delta_j \ x \ S3_{t-j} + \sum_{j=1}^{k} \phi_j \ x \ S1B_{t-j} + \varepsilon_{2t}$$

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 2, 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 5% the variable is non-stationary. Therefore, the variables are integrated of order 1.

Table 2. The ADF test

S1B		S3		S4A	
I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
H0: The time series has a unit root (non-stationary)					
0.2742	0.0000	0.4138	0.0000	0.1308	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 3). If the probability is higher than the significance level of 5%, the null hypothesis is accepted. Otherwise, the null hypothesis is rejected.

Table 3. Pairwise Granger causality test

Null hypothesis	Probabilities
D_S3 does not Granger Cause D_S1B	3.E-05
D_S1B does not Granger Cause D_S3	0.0213
D_S4A does not Granger Cause D_S1B	8.E-20
D_S1B does not Granger Cause D_S4A	3.E-06

Source: own estimations

Taking in consideration that first difference data became stationary and the Pairwise Granger test reflects causality linkages, two VAR models with 2 variables were 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.

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 4, each VAR model has 2 lags.

Table 4. Estimation of the optimal number of lags

Routes	LR	FPE	AIC	SC	HQ	Chosen lag
S1B – S3	2	2	2	1	2	2
S1B – S4A	2	3	3	2	2	2

Source: own estimations

The stability of the estimated VAR models was tested with "AR Roots Table" test which indicates that all roots are subunitary and the models are stable (Table 5).

Table 5. VAR model stability

Routes	Results	Roots modulus
S1B – S3	No root lies outside the unit circle. VAR satisfies the stability condition.	0.882138 0.774377 0.150545 0.011968
S1B – S4A	No root lies outside the unit circle. VAR satisfies the stability condition.	0.867756 0.744080 0.156842 0.045365

Source: own estimations

Regarding the quality of residuals, their normal distribution, homoskedasticity and lack of autocorrelation were tested (Table 6). If the probability is higher than the significance level of 5%, the null hypothesis is accepted. Otherwise, the null hypothesis is rejected.

Table 6. Residuals tests

S1B – S3 route		
Autocorrelation LM test		
H0 No serial correlation at lag order h		
Lag 1: 0.1818	Lag 2: 0.1629	
Cholesky (Lutkepohl) Normality test		
H0 Residuals are multivariate normal		
Skewness	Kurtosis	Jarque-Bera
0.3732	0.2171	0.2174
White Heteroskedasticity test		
H0 no heteroskedasticity		
0.1141		

S1B – S4A route		
Autocorrelation LM test		
H0 No serial correlation at lag order h		
Lag 1: 0.0534	Lag 2: 0.0403	
Cholesky (Lutkepohl) Normality test		
H0 Residuals are multivariate normal		
Skewness	Kurtosis	Jarque-Bera
0.4625	0.7458	0.7463
White Heteroskedasticity test		
H0 no heteroskedasticity		
0.5681		

Source: own estimations

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

a) $$S1B_t = \alpha_1 + \beta \text{ x } S1B_{t-2} + \chi \text{ x } S3_{t-2} + \varepsilon_{1t}$$

$$S3_t = \alpha_2 + \delta \text{ x } S3_{t-2} + \phi \text{ x } S1B_{t-2} + \varepsilon_{2t}$$

b) $$S1B_t = \alpha_1 + \beta \text{ x } S1B_{t-2} + \chi \text{ x } S4A_{t-2} + \varepsilon_{1t}$$

$$S4A_t = \alpha_2 + \delta \text{ x } S4A_{t-2} + \phi \text{ x } S1B_{t-2} + \varepsilon_{2t}$$

Table 7. VAR model estimation for S1B – S3

	D_S1B	D_S3

D_S1B(-1)	0.909362	0.065265
	(0.02457)	(0.02972)
	[37.0083]	[2.19609]
D_S1B(-2)	-0.030567	-0.033072
	(0.02445)	(0.02957)
	[-1.25023]	[-1.11842]
D_S3(-1)	0.088378	0.909665
	(0.02026)	(0.02450)
	[4.36235]	[37.1250]
D_S3(-2)	-0.057152	-0.102099
	(0.02033)	(0.02459)
	[-2.81076]	[-4.15168]
C	0.160413	-2.862417
	(4.79268)	(5.79654)
	[0.03347]	[-0.49381]
R-squared	0.801455	0.705419
Adj. R-squared	0.800986	0.704723
Sum sq. resids	65937548	96452519
S.E. equation	197.3504	238.6867
F-statistic	1708.507	1013.538
Log likelihood	-11380.75	-11703.66
Akaike AIC	13.41078	13.79112
Schwarz SC	13.42679	13.80713
Mean dependent	-3.921673	-15.64900
S.D. dependent	442.3803	439.2520

Determinant resid covariance (dof adj.)	2.16E+09
Determinant resid covariance	2.15E+09
Log likelihood	-23062.39
Akaike information criterion	27.17597
Schwarz criterion	27.20799

Source: own estimations

Table 8. VAR model estimation for S1B – S4A

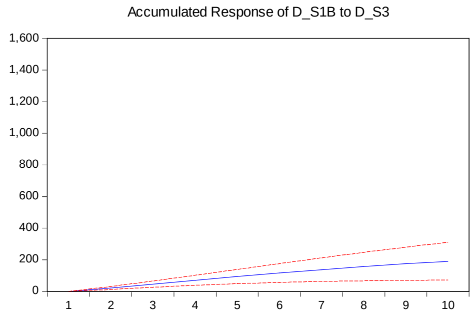
	D_S1B	D_S4A
D_S1B(-1)	0.863390	0.315631
	(0.02475)	(0.06518)
	[34.8804]	[4.84256]
D_S1B(-2)	-0.026163	-0.206513
	(0.02406)	(0.06335)
	[-1.08741]	[-3.25965]
D_S4A(-1)	0.077998	0.859922
	(0.00937)	(0.02468)
	[8.32089]	[34.8390]
D_S4A(-2)	-0.031653	-0.074253
	(0.00959)	(0.02525)
	[-3.30089]	[-2.94067]
C	0.206378	-2.742977
	(4.69548)	(12.3640)
	[0.04395]	[-0.22185]
R-squared	0.809213	0.700147
Adj. R-squared	0.808762	0.699439
Sum sq. resids	63361129	4.39E+08
S.E. equation	193.4563	509.4051
F-statistic	1795.189	988.2754
Log likelihood	-11346.91	-12990.90
Akaike AIC	13.37092	15.30730
Schwarz SC	13.38693	15.32332
Mean dependent	-3.921673	-15.12191
S.D. dependent	442.3803	929.1732

Determinant resid covariance (dof adj.)	9.32E+09
Determinant resid covariance	9.26E+09
Log likelihood	-24302.48
Akaike information criterion	28.63661
Schwarz criterion	28.66863

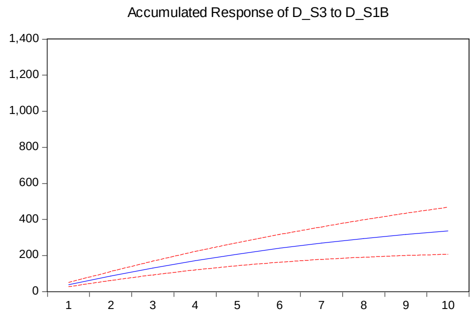
Source: own estimations

The VAR models estimated above describe the autoregressive connections between various components of Baltic Supramax Index. Based on the estimated models, the impulse-response functions can be determined. The impulse-response functions show the impact of a shock of one route on the other route and vice-versa (Figure 1 and Figure 2).

Figure 1 The impulse-response functions for S1B – S3



Source: own estimations



Source: own estimations

Figure 2. The impulse-response functions for S1B – S4A

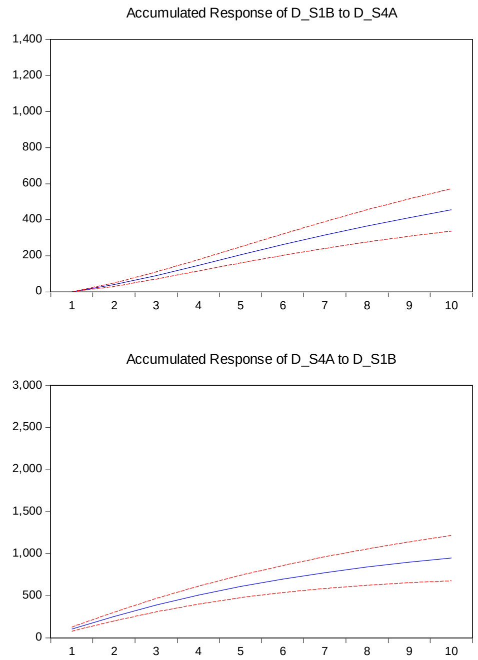


Figure 2. The impulse-response functions for S1B – S4A

Source: own estimations

5. CONCLUSIONS

Figures show that there are significant differences between regions for each individual route of the Baltic Supramax Index. Most of the times the time charter level is a consequence of the equilibrium between demand and supply of ships in the area, but there are also situations when the market raises significantly in an area and as a consequence vessels situated at a shorter or a longer distance from that area are ballasting toward the hot area and in this case they put pressure on the supply and either reduce the increase in the time charter levels from that area or reduce the time charter levels from that area. Ballasting of ships from an area to the other is also changing the equilibrium in the area they are leaving from and in turn the market in that area may start moving up or stop moving down.

As it can be noticed from Figure 1, there is a bidirectional relationship between S1B route and S3 route, and the influence of S1B route on S3 route is stronger than the reverse one. Both routes follow the same pattern during the analyzed time interval.

Figure 2 shows a symmetrical and bidirectional relationship between S1B route and S4A route, with influences of the same intensity. Also, both routes follow the same pattern during the analyzed time interval.

6. REFERENCES

[1] Alizadeh A.H., Nomikos N.K., *Shipping Derivatives and Risk Management*, Palgrave Macmillan, 2009.

[2] Stopford M., *Maritime Economics* 3rd Edition, Routledge, 2009.

[3] Xu J.J., Leung Y.T., Liming L., "Dynamic Interrelationships between Sea Freight and Shipbuilding Markets", *Proceedings of International Forum on Shipping, Ports and Airports (IFSPA 2008) - Trade-Based Global Supply Chain and Transport Logistics Hubs: Trends and Future Development*, 25-28 May 2008, The Hong Kong Polytechnic University, Hong Kong, China, pp. 480-494.

[4] Chou M.T., "Research on the relationship between forward freight agreements and the fuel oil index", *African Journal of Business Management*, Vol. 5(20), 2011, pp. 8033-8040.

[5] Bulut E., Duru O., Yoshida S., "A Fuzzy Time Series Forecasting Model for Multi-Variate Forecasting Analysis with Fuzzy C-Means Clustering", *World Academy of Science*, Engineering and Technology, 63, 2012.

[6] Ko B.W., "Analysis of Term Structure in Dry Bulk Freight Market", *The Asian Journal of Shipping and Logistics*, Volume 29, Number 1, April 2013, pp. 001-022.

[7] Nadeesha D.H.D, De Silva A.D., "A Time-Series Analysis of Export-Led shipping demand Hypothesis for Sri Lanka", *International Journal of Scientific and Research Publications*, Volume 3, Issue 9, September 2013.