APPLICATION OF AUTOREGRESSIVE MODELS FOR FORECASTING THE BALTIC EXCHANGE DRY INDEX

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ABSTRACT

The shipping industry has been growing rapidly from year to year and until not too long ago, shipping was both the greatest beneficiary and hammering pulse of globalization. But now the global economic and financial crisis has multiplied the problems of shipping industry, generating a high volatility of prices. In this context, it becomes imperious to analyze and estimate the dynamics of various indices that could be useful to capture market volatility in real time. In this respect, the Baltic Dry Index is considered to be a leading indicator of economic activity reflecting global demand for raw materials, representing a reliable and independent source of information.

Keywords: *Baltic Dry Index, shipping, volatility, shipping demand, autoregressive.*

1. INTRODUCTION

In shipping industry, exposure to unanticipated fluctuations may affect the profitability and stability of the company. Therefore, it is always prudent to apply methods and strategies which reduce uncertainty and risk. The activity of risk management in the freight markets requires the availability of reliable price information on the underlying freight market. In this respect, Baltic Exchange is the leading provider of freight-market information by producing various indices. These indices are used by many analysts to assess the states and prospects of the worldwide economic activity.

The first daily freight index was published by the Baltic Exchange in January 1985. The Baltic Freight Index (BFI) initially consisted of 13 voyage routes covering a variety of cargoes ranging from 14 000 metric tons of fertilizer up to 120 000 metric tons of coal, and was developed as a settlement mechanism for the then newly established Baltic International Freight Futures Exchange (BIFFEX) futures contract. It quickly won worldwide acceptance as the most reliable general indicator of movements in the dry-cargo freight market. Over the years, the constituent routes of that original index were refined to meet the ever-increasing and changing needs of the derivative markets [1].

The Baltic Dry Index (BDI) is the successor to the Baltic Freight Index (BFI) and came into operation on 1 November 1999. Since the 1st of July 2009, the Index is a composite of the Capesize, Panamax , Supramax and Handysize Timecharter Averages.

The calculation until the 30th of June 2009 was based on an equally weighted average of the BCI, BPI, BHSI and the BSI index, which superseded the BHMI on 03 January 2006, which superseded the BHI on 2 January 2001. The BDI continues the established time series of the BFI, introduced in 1985.

For the creation of BDI the following formula is used:
((CapesizeTCavg + PanamaxTCavg + SupramaxTCavg + HandysizeTCavg)/ 4)) * 0.113473601
where TCavg = Time charter average.

The multiplier was first applied when the BDI replaced BFI, and has changed over the years as the contributing indices and the methods of calculation have been modified.

The Baltic Dry Index is considered to be a leading indicator of economic activity reflecting global demand for raw materials, representing a reliable and independent source of information. The BDI may be considered a predictor because its variation has a strong association with the commodities market. Since BDI is only operated by actual buyers and/or sellers, there is no speculative part concerning this index. Furthermore, the BDI is now revised and is highly accurate with the daily updates. The BDI can be seen as an equilibrium price of the dry bulk shipping market.

2. LITERATURE REVIEW

Although the academic literature on the BDI has a long history, recent research papers on this subject are scarce.

Theodoulidis and Solís (2009) attempt to identify trends or stages in the BDI associated with economic cycles, as well as other relationships with economic indicators. The authors apply data mining techniques on a dataset consisted of prices for economic indicators from January 1985 to December 2008, including monthly average prices of Copper, Oil, Gold, Silver and the Dow Jones Industrial monthly index values. The models developed in their paper have an average power of classification of 72% in an out-of-sample set and may be used to analyze the current status of the freight market in terms of the economic cycles. Furthermore, the final results highlight that, during recent years, BDI has been more linked with the copper prices and that usually stock market prices have a limited effect on it.

Chung and Ha (2010) investigated the effect of the global financial crisis on the Baltic Dry Index by using the error correction model. Their empirical research highlight that there has been a co-integration relationship between the BDI and certain explanatory variables such as China’s iron import, Eurodollar interest rate and U.S. stock price.

Wong et al. (2010) assess the influence of the Baltic Dry Index on the bulk shipping industry from the demand prospective by applying Grey Relational Analysis with the Entropy method. The research results show that the fluctuation of international steel prices is most closely connected with the BDI, followed by fuel prices, grain prices and coal prices.

Bakshi et al. (2011) try to demonstrate that the Baltic Dry Index has predictive ability for a range of stock markets by applying through in-sample tests and out-of sample statistics. The authors show that the three-month growth rate of BDI is a predictor of global stock market returns, commodity index returns and growth in global real economic activity. Their analysis is carried out with data collected from four MSCI regional stock market indexes, as well as the individual stock markets in the G-7 countries, 12 other developed and 12 emerging market economies, and US dollar-denominated returns.

As an overall economic indicator, BDI is especially relevant for the trade of the less developed countries that export mostly primary goods, relying on bulk carriers for international transportation. Apergis and Payne (2013) examine the information and predictive content of the BDI for both financial assets and industrial production by using panel data methods for the period 1985 2012. Overall, their research highlights the relevance of the BDI as an indicator that captures the variations across financial asset market and the macroeconomy.

Papailias and Thomakos (2013) investigate the cyclical properties of the annual growth of BDI and their implications for short-to-medium term forecasting performance. The authors show that the index has a cyclical pattern which has been relatively stable across time. Furthermore, BDI is negatively synchronized with a weaker dollar and the spread of the US Treasuries and positively synchronized with the GBP/USD exchange rate, the emerging market equities, copper and tin. Also, the authors perform a forecasting performance evaluation by using a variety of models and a 12-month investment exercise which can be useful in building a reliable risk management system.

3. DATA AND METHODOLOGY

In this study, the ARIMA models were applied in order to analyze and forecast the dynamics of the Baltic Exchange Dry Index. The daily data series of Baltic Exchange Dry Index for the period 04.01.1985 – 16.09.2013 were used for the empirical study, comprising 7209 observations. Data were collected from Baltic Exchange database and the ARIMA models were built with EViews 7.

The ARIMA model is a generalization of the autoregressive and the moving average models. The autoregressive (AR) model uses past values of the dependent variable to explain the current value whereas, the moving average (MA) model uses lagged values of the error term to explain the current value of the explanatory variable.

The general ARIMA model is called an ARIMA(p,d,q), with “p” being the number of lags of the dependent variable (the AR terms), “d” being the number of differences required to take in order to make the series stationary, and “q” being the number of lagged terms of the error term (the MA terms). An ARIMA(p,d,q) (AutoRegressive Integrated Moving Average with orders p,d,q) model is a discrete time linear equations with noise, of the form:

$$\left(1-\sum_{k=1}^{p}\alpha_k L^k\right)(1-L)^d X_t = \left(1+\sum_{k=1}^{q}\beta_k L^k\right)\varepsilon_t$$

4. EMPIRICAL ANALYSIS

In the first instance, 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 be absorbed. The existence of a unit root was estimated for the original data and the absence of a unit root for the first-difference data (Table 1). Therefore, the variables are integrated of order 1 and denoted by l(1).

Table 1. The ADF test for first-difference logarithmic data

Null Hypothesis: D_BDI has a unit root
Exogenous: Constant
Lag Length: 10 (Automatic - based on SIC, maxlag=34)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-17.22347	0.0000
Test critical values:	1% level	-3.431081	
	5% level	-2.861748	
	10% level	-2.566922	

*MacKinnon (1996) one-sided p-values.

Source: own estimations

If the probability is lower than the significance level, the null hypothesis is rejected. It can be observed that the first-difference data is stationary for a 1% significance level.

In order to select the appropriate ARIMA model, the Box-Jenkins approach, which is a three-stage method, comprising identification, estimation and diagnostic checking, will be applied.

In the identification stage, the form of the model has to be identified, because any model may be given more than one different representations. Once the time series stationarity is achieved, the next step is to identify the “p” and “q” orders of the ARIMA model. Therefore, the time plot of the series autocorrelation function (ACF) and partial correlation function (PACF) will be visually analyzed, because they provide useful information regarding outliers, missing values and structural breaks in the data (Table 2).

From the table below, it can be observed that there are three significant spikes on the time plot of the series autocorrelation function (ACF), and then all are zero, while there are two significant spikes in the partial correlation function (PACF). This suggests that the models might have up to MA(3) and AR(2) specifications. Thus, the possible models are the ARIMA(1,1,1), ARIMA(1,1,2), ARIMA(1,1,3), ARIMA(2,1,1) ARIMA(2,1,2), ARIMA(2,1,3) models.

Table 2 Autocorrelation function and partial correlation function

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.801	0.801	4629.1	0.000
		2	0.519	-0.343	6573.1	0.000
		3	0.295	0.035	7200.5	0.000
		4	0.166	0.046	7398.7	0.000
		5	0.106	0.012	7479.4	0.000
		6	0.101	0.071	7552.3	0.000
		7	0.129	0.062	7671.7	0.000
		8	0.153	0.009	7840.7	0.000
		9	0.161	0.025	8027.3	0.000
		10	0.161	0.043	8214.4	0.000

Source: own estimations

According to Box and Jenkins, a valid model should be stationary and invertible. Therefore, the modulus of each AR coefficient has to be lower than 1, the sum of AR coefficients has to be lower than 1 and the modulus of each root has to be lower than 1. These requirements are fulfilled by all the models, excepting ARIMA(2,1,1). Furthermore, the ARIMA(1,1,3) model has the MA(3) term insignificant, the ARIMA(2,1,2) model has the AR(2) term insignificant and the ARIMA(2,1,3) model has the AR(1) term insignificant. Therefore, these models will be dropped.

The remaining models are estimated and analyzed in the estimation stage. The estimated models are compared using the Akaike information criterion (AIC), the Schwartz Bayesian criterion (SBC) and Adjusted R-squared (Table 3). The model that has the smallest AIC and SBC and the highest Adjusted R-squared will be chosen.

Table 3. Summary results of possible ARIMA models

Model	**ARIMA(1,1,1)**	**ARIMA(1,1,2)**
AIC	9.345529	9.328810
SBC	9.348394	9.332630
Adjusted R-squared	0.679482	0.684840

Source: own estimations

According to Table 3, all the criteria suggest that the fit model is ARIMA(1,1,2).) The model is estimated in Table 4 and its validity is tested in Table 5. It can be noticed that the model is stationary and invertible. Also, R-squared and Adjusted R-squared tests are higher than 50%.

Table 4. Estimation of ARIMA(1,1,2) model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.095963	1.214214	0.079033	0.9370
AR(1)	0.578458	0.016022	36.10285	0.0000
MA(1)	0.507971	0.018358	27.67012	0.0000
MA(2)	0.185062	0.016328	11.33417	0.0000

R-squared	0.684972	Mean dependent var	0.090606
Adjusted R-squared	0.684840	S.D. dependent var	45.71960
S.E. of regression	25.66656	Akaike info criterion	9.328810
Sum squared resid	4745137.	Schwarz criterion	9.332630
Log likelihood	-33612.37	Hannan-Quinn criter.	9.330124
F-statistic	5220.534	Durbin-Watson stat	1.998265
Prob(F-statistic)	0.000000		

Inverted AR Roots	.58	
Inverted MA Roots	-.25+.35i	-.25-.35i

Source: own estimations

Table 5. ARIMA(1,1,2) structure

AR Root(s)	Modulus	Cycle
0.578458	0.578458	

No root lies outside the unit circle.
ARMA model is stationary.

MA Root(s)	Modulus	Cycle
-0.253985 ± 0.347208i	0.430188	2.852936

No root lies outside the unit circle.
ARMA model is invertible.

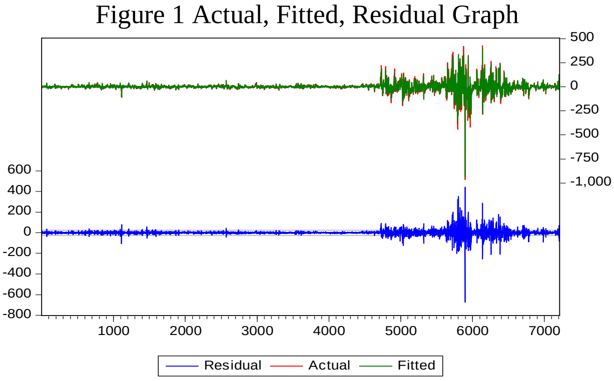
Source: own estimations

In the last stage, the goodness of fit of the model is examined. Therefore, the statistical significance of model's coefficients, the quality and the autocorrelation of residuals will be tested.

As it can be observed from Table 4, all the coefficients are statistically significant for a 1% significance level.

Regarding the quality of residuals, the best view to look at first is Actual, Fitted, Residual Graph (Figure 1). It can be noticed that the fit is very good and the fitted values almost cover up the actual values.

Figure 1 Actual, Fitted, Residual Graph



Source: own estimations

According to the correlogram of residuals (Table 6), since there are no significant spikes of ACFs and PACFs, it means that the residuals of the selected ARIMA model are white noise, so that there are no other significant patterns left in the time series.

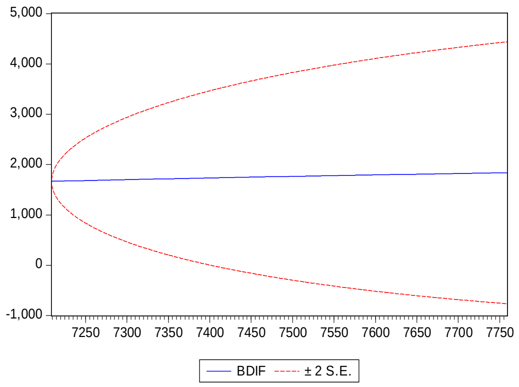
Table 6. Correlogram of residuals

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.001	0.001	0.0054	
		2	0.002	0.002	0.0352	
		3	0.002	0.002	0.0600	
		4	-0.013	-0.013	1.3175	0.251
		5	-0.024	-0.024	5.3917	0.067
		6	-0.018	-0.018	7.6739	0.053
		7	0.043	0.043	20.874	0.000
		8	0.053	0.053	41.249	0.000
		9	0.040	0.039	52.688	0.000
		10	0.010	0.009	53.460	0.000

Source: own estimations

Taking in consideration the results of the tests applied to the estimated model, it can be concluded that the ARIMA(1,1,2) model is appropriate. By using this model, the Baltic Exchange Dry Index will be forecasted for the period October 2013 – December 2015. Figure 2 illustrates the dynamic forecast of BDI and its error margins.

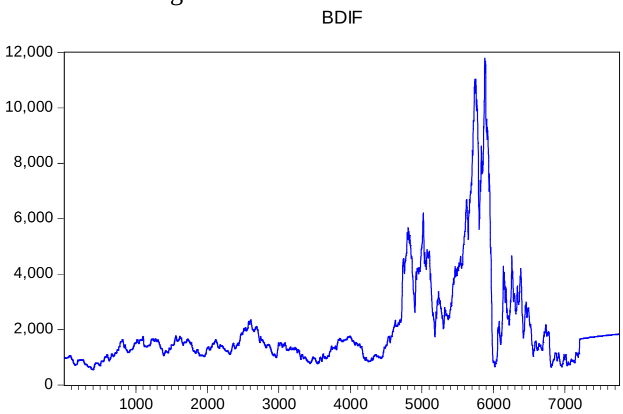
Figure 2. Dynamic forecast of BDI



Source: own estimations

Figure 3 presents the fluctuation of BDI from January 1985 to December 2015

Figure 3.The evolution of BDI



Source: own estimations

5. CONCLUSIONS

As it can be noticed from Figure 3, the dry-freight rates recorded a gradual increase after January 2003 and from that period onwards the market volatility has increased. During 2008, the financial crisis affected the shipping industry due to the fact that many industrial producers reduced or stopped their production. On 20th May 2008 the BDI reached 11 793 points, its all time high. A few months later, the index began to fall and in 7 months lost 95% of its value, dropping to 663 points – the lowest point since 5th December 2008. The index is extremely volatile in the last decade compared to the first 18 years of existence, due to worldwide economic booms and recessions. The trend of the forecasted values of BDI can be easily visualised (starting with observation no. 7000), showing a slight increase during the next two years.

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