

A Service of

ZBW

Leibniz-Informationszentrum Wirtschaft Leibniz Information Centre for Economics

Geomelos, N. D.; Xideas, E.

# Article

# Forecasting spot prices in bulk shipping using multivariate and univariate models

**Cogent Economics & Finance** 

Provided in Cooperation with:

Taylor & Francis Group

*Suggested Citation:* Geomelos, N. D.; Xideas, E. (2014) : Forecasting spot prices in bulk shipping using multivariate and univariate models, Cogent Economics & Finance, ISSN 2332-2039, Taylor & Francis, Abingdon, Vol. 2, Iss. 1, pp. 2-37, https://doi.org/10.1080/23322039.2014.932701

This Version is available at: https://hdl.handle.net/10419/147718

# Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.



http://creativecommons.org/licenses/by/3.0/

#### Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.







# **RESEARCH ARTICLE**

# Forecasting spot prices in bulk shipping using multivariate and univariate models

N.D. Geomelos and E. Xideas

Cogent Economics & Finance (2014), 2: 932701









Received: 14 November 2013 Accepted: 01 June 2014 Published: 08 July 2014

\*Corresponding author: N.D. Geomelos, Department of Shipping, Trade and Transport, University of the Aegean, G. Veriti 84, Chios 82100, Greece E-mail: n.geomelos@chios.aegean.gr

Reviewing Editor: David McMillan, University of Stirling

Further author and article information is available at the end of the article

# **RESEARCH ARTICLE** Forecasting spot prices in bulk shipping using multivariate and univariate models

N.D. Geomelos<sup>1\*</sup> and E. Xideas<sup>1</sup>

Abstract: This paper employs an applied econometric study concerning forecasting spot prices in bulk shipping in both markets of tankers and bulk carriers in a disaggregated level. This research is essential, as spot market is one of the most volatile markets and there is a great uncertainty about the future development of spot prices. This uncertainty could be reduced by using estimates of ex-post and ex-ante forecasts. Econometric analysis focuses in the comparison of different econometric models from two important categories of econometrics: (1) multivariate models (VAR and VECM) and (2) univariate time series models (ARIMA, GARCH and E-GARCH) in order to derive the best predicting model for each ship type. Also, forecasts can be modified to yield an improved performance of forecasting accuracy via the theory of combining methods. Ex-post and ex-ante forecasts are estimated on the basis of best predicting model's performance. Results show that the combining methodology can reduce even more the forecasting errors. The results of empirical analysis could also be useful from the specialization, identification, estimation, and evaluation of previous econometric models' point of view. Also, ex-ante forecasts, which are taking into consideration the present economic crisis, can be used for the formation of efficient economic policy from decision-makers of shipping industry reducing even more spot markets' risk.

Keywords: C32—time-series models, C0—general, A—general economics and teaching, C52—model evaluation and testing

# AUTHOR BIOGRAPHY

N.D. Geomelos Economist, Applied Econometrician—Researcher (Department of Shipping, Trade and Transport, University of the Aegean, Greece). His dissertation on Applied Economics and Econometrics has as a topic "Applied Techniques of Econometric Forecasting in Shipping Markets". His researching interests extend to applied econometrics, macroeconomics analysis, and international trade. He has been awarded grants for his studies from the National Foundation of Scholarships in Greece. He has graduated from the National School of Artillery with the rank of Second Lieutenant.

# PUBLIC INTEREST STATEMENT

This paper examines analytically two categories of applied econometrics' models, multivariate and univariate time-series models. The research realizes a systematic econometric analysis to compare and to propose specific quantitative economic relations, which are developed among the spot market of shipping industry. Analysis also uses the estimates and the results of models to generate ex-post and ex-ante forecasts, so much in the sample as beyond the original estimation period. The estimation sample includes monthly observations from the beginning of 1970s until the beginning of 2011. The generated forecasts are not limited in one vessel type, but they extend according to a disaggregated analysis in both tanker (five vessel types) and dry bulk markets (three vessel types). The results show that multivariate models give more precise forecasts revealing the relation of interdependence and feedback, which exists among the shipping markets. Combining forecasting methodology provide lower forecasting errors in spot market.





 $\odot$  2014 The Author(s). This open access article is distributed under a Creative Commons Attribution (CC-BY) 3.0 license.

#### 1. Introduction

Shipping is characterized by complexity and uncertainty as it is one of the most globalized industries in the world. It is influenced by a number of endogenous variables such as the freight market, the total fleet capacity, the orderbook of newbuildings, the secondhand and newbuilding prices, and exogenous variables, such as the world GDP, the oil price, and the seaborne trade. Shipping is an unpredictable industry where adapting mechanisms never work at the same way. It is a high-cost industry where world economies (directly) and seaborne trade (indirectly) play the most important role in its development.

Shipping is differentiated in two main categories according to, (1) capacity and (2) shipping routes. The differentiation of capacity is based on the adjustability of vessels to the type of cargo, the depth of ports, and mainly in the utilization of economies of scale. The appropriate choice of vessels' deadweight is crucial and it is related to the building and operating cost of each ship type. Also, the differentiation of shipping routes is based on ton-miles, which they are related to the consumption of oil and consequently to the total cost of vessels.

Bulk shipping is constituted by two main markets, the tanker market and the bulk carrier market where the majority of cargoes are transferred. Crude oil and its products are transported with tanker vessels (liquid cargo) and bulk carriers are used for the transportation of dry cargoes such as iron-ore, fertilizers, grain, and lumber. The transportation of these goods is essential for the world economies and the role of shipping is very crucial in that point. Shipping is the most efficient and competitive transport mean as it has the best cost performance in relation to railway and air transportation as shipping transfer approximately 80% of the world international trade (UNCTAD-Review of Maritime Transport, 2011).

Ship owners are trading in four shipping markets (freight, secondhand, newbuilding, and scrap) and their decisions affect the supply of shipping services in many ways. Most of their decisions are based on the level of freight rates, adapting their investment plans according to the phase of shipping cycle. The evolution of shipping cycles is reflecting the evolution of freight market, where the short-term and the long-term decisions of decision-makers are determining the cyclicality of shipping cycle. A shipping cycle shows very distinctively that a shipping market has its ups and downs, which lead to unpredictable fluctuations and finally to uncertainty.

Uncertainty is spread to shipping industry affecting expectations about the demand and the supply of shipping services. Expectations are also related to the yield of capital assets (ships). Thus, uncertainty has consequences in the procedure of decision-making behavior. For example, the ship owner must decide which of two markets (spot or time charter market) is more profitable for his fleet. And there is a substantial risk in this decision, as it is impossible for someone to know the future of world economy and especially that of seaborne trade. In a period of recession and fierce economic crisis, uncertainty in shipping markets becomes even bigger. A ship-owner take a decision to build a new vessel, but this decision assumes high risk as the business might fail and the initial investment may be lost. For this reason, many decision-makers try to interpret the spot market in high-cost/high-risk view.

Spot market is the source of revenues for shipping companies and its importance has been examined by many economists diachronically. Every economic analysis aims to reduce the risk and in general the uncertainty of spot markets applying various economic theories. But the existing economic theories have very limited interpretation of the operation of economic systems and they cannot support decision-makers to achieve the most productive economic efficiency. In a market like shipping which operates under uncertainty, it is necessity for economists to apply econometric models to evaluate their decisions. Therefore, they must adopt the appropriate econometrics' methodology to forecast the future track of spot markets.

Forecasts and decision theory are usually linked together with feedback effects. Neither forecasting nor decision theory can work separately. Decision-makers must not rely only on their knowledge or their insight, but they also must use econometric forecasting techniques. Forecasting is even more difficult in case of shipping industry as it is one of the most stochastic economic environments. This paper is based on the hypothesis of stochastic properties of shipping markets and analyzes different methodologies of econometric forecasting and especially analyzes the following models: (1) Vector AutoRegressive (VAR), (2) Vector Error Correction Model (VECM), (3) AutoRegressive Integrated Moving Average Models (ARIMA), (4) Generalized AutoRegressive Conditional Heteroskedasticity (GARCH), and (5) Exponential GARCH (E-GARCH).

The aim of this paper is to create econometric models which are adapted to the complicated reality of shipping industry. Econometric research concerns both tankers and bulk carriers markets in a disaggregated analysis with eight different vessel types (Tankers: ULCC-VLCC, Suezmax, Aframax, Panamax, Handysize—Bulk carriers: Capesize, Panamax Bulk, Handymax). Models are focused on dynamic properties of shipping system taking into account the cyclical fluctuations of economic and shipping cycles using dynamic multipliers and dynamic elasticities.

# 2. Literature review

The essay about the mechanism of freight rates is one of the most crucial points in the shipping industry. In fact, the nature of the industry raises a point to carry out a number of researches and studies. Uncertainty and implied volatility of freight prices are the main motives, which lead the researchers to discover more appropriate quantitative methods to decipher the market.

It is important to be noticed that the majority of economists have been studied, in most cases, the equilibrium of shipping markets during the last two decades (Beenstock & Vergottis, 1993; Tsolakis, 2005). They analyzed the shipping markets as a static mechanism where a system of variables must link together supply and demand into balance. Most theories, which were dedicated in market's equilibrium, come from this static notion about shipping economy. However, this concept about equilibrium can be used only as a very simple explanatory tool in contrast to a very complicated reality which underlies disharmony fluctuations and lack of balance.

New studies are focused on dynamic systems which exploit the development of econometrics. The dynamic nature of models interprets shipping markets in better way and it helps to understand the mechanism of markets by producing more accurate forecasts (Hawdon, 1978). Many modern economists lay the foundation of dynamic analysis of shipping markets and especially that of spot market combining the traditional view of equilibrium with the new techniques of econometric analysis.

Veenstra and Franses (1997) produce forecasts for Panamax dry bulk carrier using the issue of cointegration relation among spot rates of six different shipping routes. Their methodology is based on the existence of cointegration relations and spot market's efficiency using a VAR model. This model doesn't include other endogenous or exogenous variables, because the authors consider the spot market as efficient. This hypothesis leads to large forecast errors, because of the existence of common stochastic trend among the six different time series of routes.

Randers and Göluke (2007) create an aggregate model of interpretation of tanker market without any discrimination in vessel size or shipping routes. Their model is focused on the total fleet capacity and the way of utilization of that capacity. Cyclicality and volatility of spot market are not exogenous variables, because they are not influencing from the economic changes but from the market itself and hence they have been treated as endogenous. Many researchers and academics support that the disturbances of volatility of shipping markets are largely due to events, which occur outside the shipping sector such as wars, canal closings, oil prices, and legislation (Stopford, 1997). They also claim that the shipping community creates the cyclicality and especially its own investment decisions create the volatility of shipping environment. This phenomenon is known as self-infliction view. Authors' forecasts are based on the shipping cycle's analysis and they believe that the long-term forecasts are possible mainly from 1 to 4 years. For shorter periods of time there is too much noise from the changes of exogenous variables where the forecasts are inaccurate. Scarsi (2007) underlines the unstable nature of dry bulk market because of the economic and geopolitical changes. He supports that when the economy grows, then the demand of cargoes is increased following the definition of derived demand. It is obvious that according to shipping cycle, ship owner must take into account two very serious decisions. The first is related to the operation of ships and the second with the asset play. Scarsi believes that it is difficult to produce reliable forecasts because the volatility of shipping is depended on exogenous factors like the delivery of a ship after two or four years. During this time period, the conditions of freight market have already changed.

Except the previous studies, a different approach of freight market analysis is realized using the Forward Freight Agreement (FFA) market. The forward freight market determines the equilibrium prices in spot market during the price discovery process. According to price discovery, efficient information about the future price of asset can be obtained through future markets. In shipping industry, price discovery is used for the determination and the forecasting of spot rates using only one variable that of forward rates. Kavussanos and Nomikos (1999) use four forecasting models (VECM, ARIMA, Exponential Smoothing, and Random Walk) in the freight futures market. They also examine the short-run dynamic properties of spot and futures prices in order to specify the speed which responds to deviations from their long-run relationship. They propose VECM model as the best forecasting model in the contrary of Cullinane (1992) who proposes ARIMA models. The final conclusion is that the hypothesis of unbiasedness is based on the unbiasedness of future contract's price in relation to the realized spot price. This confirms the significance of future rates to spot prices. Their final conclusion is that the future prices react more quickly in the changes of market in relation to the spot prices.

Kavussanos and Visvikis (2004) re-examine the price discovery and especially the lead-lag relationship between current spot rates and FFA. They use a multivariate model VECM combined with a GARCH model. Variances and covariances of time series are varied from time to time allowing the spill-over effect between spot and derivatives markets. According to authors, this methodology gives better forecasting performance and market analysis is improved.

Batchelor, Alizadeh, and Visvikis (2007), in a similar methodology, show that ARIMA or VAR models forecast the future prices with smaller forecast errors, but using different samples from the study of Kavussanos and Nomikos. The differentiation of results is obviously based on different samples.

A new methodology for the prediction of spot prices is the Artificial Neural Network (Lyridis, Zacharioudakis, Mitrou, & Mylonas, 2004). This technique follows the multivariate analysis with exogenous variables which affect the level of spot prices. Authors support that in an industry as dynamic as shipping, multivariable models interpret more precisely the freight markets in relation to univariate models.

# 3. Methodology

Firstly, the issues of stationarity and seasonality are considered in order to investigate the forecasting performance of univariate and multivariate models of spot prices in bulk shipping.

# 3.1. Stationarity

n 1

Stationarity implies that the distribution of the variable under consideration does not depend upon time or in other words the variances and autocovariances are finite and independent of time.

It is of great importance for the analysis to test the order of integration of spot prices. For univariate time-series models, spot prices must be stationary or integrated of order zero—I(0,0).<sup>1</sup> This analysis implements the three most used statistical tests according to Lutkepohl and Kratzig (2004). The first test is Augmented Dickey-Fuller (ADF) where tests the pair of hypotheses H<sub>0</sub>:  $\varphi = 0$  and  $\beta = 0$  (stochastic trend) versus H<sub>1</sub>: $\varphi < 0$  and  $\beta \neq 0$  (deterministic trend) and estimates the following regression:

$$\Delta \mathbf{y}_t = \varphi \mathbf{y}_{t-1} + \beta_t + \sum_{j=1}^{p-1} \alpha_j^* \Delta \mathbf{y}_{t-j} + \varepsilon_t \tag{1}$$

Model with time trend an	d constant term	
Test equation: $\Delta Y_t = \varphi +$	$\beta_t + \rho Y_{t-1} + \sum_{i}^{\rho} \lambda i \Delta Y_{t-1} +$	u <sub>t</sub>
Sample size	<i>F</i> -test	Critical values 5% level (t-statistic)
50	6.73	-3.49
100	6.49	-3.45
[500]	[6.30]	[-3.42]
∞	6.25	-3.41

Source: Author (adaptation from Heij, De Boer, Franses, Kloek, and Van Dijk [2004]).

where  $\varphi = -\alpha(1)$  and  $\alpha_j^* = -(\alpha_{j+1} + \dots + \alpha_p)$ . ADF test is based on *t*-statistic and critical values have been obtained by Davidson and MacKinnon (1993).

The second test known as Philips–Perron (PP) is an alternative to the ADF test. The adoption of PP test from the current paper lays to the fact that the test covers the case of series which have structural breaks (Perron, 1989).

For ADF and PP tests, it is checked the hypothesis  $H_0$ :  $\beta = \rho = 0$  for the following model according to *F*-statistic:

$$Y_t = \varphi + \sum_{i}^{\rho} \lambda_i \Delta Y_{t-1} + \varepsilon_t$$
<sup>(2)</sup>

The econometric analysis of this research is also examines a third test known as Kwiatkowski-Philips-Schmidt-Shin (KPSS) test. This test examines as null hypothesis that the data generating process is stationary  $[H_0: y_t - I(0)]$  against the alternative that it is  $[H_1: y_t - I(1)]$ . KPSS test is not appropriate for large samples and its application is questioned in models with a large number of observations as Caner and Kilian (2001) and Kuo and Tsong (2004) notice. However, this paper applies this test in order to test the accuracy of previous results in shipping data.

The paper also takes into consideration the significance of constant term considering the existence of unit root. The null hypothesis is that  $H_0$ :  $\varphi = \rho = 0$  and *F*-statistic and *t*-statistic critical values are included in Table 1.

#### 3.2. Seasonality

Another important parameter for univariate models is the examination of seasonality. Seasonality can be identified by observing regular peaks in the sample autocorrelation function (SACF). Also, the partial autocorrelation function (PACF) provides additional information about the seasonality of time-series. More specifically, the SACF exhibits peaks in lags 12, 24, 36, 48, etc. and the PACF exhibits a strong positive peak in first lag and negative peak in lag 13 (Figure A1-Appendix, U-VLCC market shows seasonality in contrary to Capesize market which hasn't shown any form of seasonality).

After the confirmation of seasonality, it is important to follow a deseasonalized procedure. This paper follows the seasonal adjustment estimating the seasonal indices by removing the seasonal variations.<sup>2</sup> This method has the advantage that eliminates the seasonal variation, while the long-run trend and short-run irregular fluctuations remain.

#### 3.3. Multivariate model VAR-VAR-X

VAR model implies univariate ARMA models for each of its components and simultaneous estimation of variables with their lags may lead to more parsimonious and fewer lags in relation to ARMA models. This simultaneity will produce better forecasts at least in short-term period (Verbeek, 2004). Also, VAR models impose linearity, which is not required in structural models (Boero, 1990). With a VAR, it is necessary to specify only two things, (1) endogenous and exogenous<sup>3</sup> variables and (2) the number of lags in order to capture the interdependence among the variables (Litterman, 1984).

An extensive research must be done in order to characterize the estimated variables as endogenous or exogenous during the construction of VAR models. This research is based on Hausman test for endogeneity (Hausman, 1983), and has as a final aim to reduce the Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) criteria of VAR models. The differentiation of variables according to Hausman test leads to more accurate ex-post forecasts with smaller forecasting errors. The results of Hausman test is presented in Appendix (Table A2).

The lag structure implies an important aspect of model specification and testing. The largest number of lags needed to VAR or VECM models must capture most of the effects that the variables have on each other. With monthly data, lags up to 6 or 12 months are likely to be sufficient according to Pindyck and Rubinfeld (1998). Also, it is widely acceptable that the choice of time lag must be based on SIC and Hannan–Quinn Criterion and less to AIC. On the contrary, AIC seems to be more reliable to infinite orders autocorrelations, Kilian (2001).

Also, another proposed method of VAR–VECM specification and selection of lag orders is by minimizing AIC or SIC (Heij et al., 2004). In practice, the lag order of VAR model is chosen relatively small, as otherwise the previous criteria become large. One method to reduce the number of parameters is by considering the possible exogeneity of some of the variables, as described by Hausman test. This method of model specification is followed by this paper.

In this paper, VAR-X models are estimated for all ship types. VAR-X models are a special case of VAR models as apart from endogenous variables they also include exogenous variables. The VAR-X models can be expressed as:

$$\Delta Y_{t} = \varphi + \sum_{i=1}^{p} a_{i} \Delta y_{t-i} + \sum_{j=1}^{q} \gamma_{j} X_{t-j} + \varepsilon_{t}$$
(3)

where  $\alpha_i$  are  $p \times p$  matrices of endogenous variables and  $\gamma_j$  are  $1 \times q$  matrices for exogenous variables. More specifically, for each ship type, an extensive empirical research have been conducted into different combinations of variables in order to minimize the Theil's inequality coefficient according to SIC criterions and Hausman exogeneity test.

#### 3.4. Multivariate models VECM

When the variables in VAR models are integrated of first or higher order, then estimation faces the problem of multiple regressions models known as spurious regression problem. The presence of non-stationary variables increases the possibilities to specify cointegration relations. The existence of cointegration relations creates the VECM models (Lutkepohl & Kratzig, 2004).

This paper uses the cointegration test as developed by Johansen (1991).

The VECM model is expressed as:

$$\Delta Y_t = -\Phi(1)(Y_{t-1} - \mu) + \sum_{j=1}^{p-1} \Gamma_j \Delta Y_{t-j} + \varepsilon_t$$
(4)

The deviations of  $Y_{t-1}$  from the equilibrium value  $\mu$  are corrected by the multiplier matrix  $-\Phi(1)$ . If the variables deviate from the long-run equilibrium, the error correction term will be non-zero. In this case, the variables adjust to a new equilibrium relation. Model specification follows the method of VAR models as described in previous part.

#### 3.5. Univariate models

Bibliography in econometrics separates the univariate models in two categories. The first category includes ARMA models where the variance of residuals is constant and the second includes GARCH models where the residuals have variable variance. Univariate time series models try to interpret the various economic phenomena using only the past behavior of dependent variable.

Newbold (1983) refers very distinctively about times series models:

"Time series models' building is not an attempt to make the data fit a particular number, but rather to make a model that fits the data."

In other words, the data process in time continuity is the crucial factor in order to choose the appropriate univariate time series model.

#### 3.5.1. ARMA models

In this paper, Box–Jenkins methodology is followed (Box & Jenkins, 1976). Model specification and especially the determination of AR and MA orders are based on the principles of parsimony and over-fitting.

The quantitative form of an ARIMA model is:

$$Y_t = \sum_{t=1}^{p} \varphi_i Y_{t-1} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j}$$
(5)

where p and q are the orders of AR and MA terms respectively and  $\varphi_i$  and  $\theta_j$  the fixed coefficients. The order of homogeneity is zero as spot rates are stationary for all markets.

Many time-series which are estimated in monthly basis as in this paper may present seasonality. In this case, seasonal autoregressive (SAR) and seasonal moving average (SMA) terms are used. The results of estimations are presented using the lag operator L according to the following equation:

$$(1 - \alpha_1 L - \alpha_2 L^2 - \dots - \alpha_i L^i)(1 - \varphi L^{12}) = (1 - \beta_1 L - \beta_2 L^2 - \dots - \beta_j L^j)(1 - \theta L^{12})\varepsilon_t$$
(6)

where the parameters  $\varphi$  and  $\theta$  are associated with the seasonal part of the process and  $\alpha$  and  $\beta$  are the orders of AR and MA terms, respectively.

#### 3.5.1.1. Diagnostic Tests

Once apparent stationarity has been tested (all spot series have been tested and they are stationary at their level), the next step is to identify the orders of the ARIMA process. Cuthbertson, Hall, and Taylor (1992, pp. 95–96) propose to test the correlograms of SACF and the PACF which help to recognize the orders of AR and MA by the spikes and the exponential decay or damped sine-wave behavior. For high-order ARIMA process, the specification of AR and MA orders becomes more difficult and requires close inspection of the full and PACFs. The diagnostic checking via *Q*-statistic calculates the autocorrelation function of the estimated ARMA model and determines whether those residuals appear to be white noise. Paper follows this procedure but also is taking into consideration the thoughts of Pindyck and Rubinfeld (1998). They support that when two or more specifications pass the diagnostic checks, it is better to compare the forecasted series with the actual series. The specification that yields the smallest forecasted errors will be retained.

Diagnostic checking for the examination of the goodness of fit of ARMA models uses Ljung–Box (LB) *Q*-statistic and Breusch–Godfrey (BG) statistic. LB statistic tests if the residuals are white noise and BG statistic tests the serial correlation of residuals. All tankers satisfy both LB and BG tests and they do not present any autocorrelation. Bulk carriers only show a small autocorrelation in residuals in Panamax Bulk but according to *Q*-statistic the residuals are white noise. (Appendix-Tables A5 and A6).

# 3.5.2. ARCH-GARCH models

The models where residuals have variable variance are known as ARCH and GARCH and it is necessary to examine the implication of these models in spot markets which are characterized by intense volatility.

In general, an ARCH model is expressed as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \alpha_p \varepsilon_{t-p}^2$$
(7)

where  $\alpha_0 = \text{constant term and } \varepsilon_t / Y_{t-1} \sim N(0, \sigma_t^2)$ .

GARCH models have a more general form, as apart from the time lags of disturbance's term variance; time lags of variance are also examined. A simple GARCH (1,1) is written as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \lambda_1 \sigma_{t-1}^2 \tag{8}$$

where  $\alpha_0$  is the constant term,  $\alpha_1$  is the last's period volatility (ARCH term), and  $\lambda_1$  is the last's period variance (GARCH term).

E-GARCH models have two important advantages in relation to GARCH models. The first is that it is possible, the examination of asymmetric innovations and the second is that the disturbance error cannot have negative variance as the variance is expressed by logarithms.

An EGARCH (1,1) model is written as:

$$\log \sigma_t^2 = a_0 + a_1 \log \sigma_{t-1}^2 + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta \frac{|\varepsilon_{t-1}|}{\sigma_{t-1}}$$
(9)

If  $\gamma$ <0, the negative shocks (bad news) generate more volatility than positive shocks (good news) and vice versa.

Also, financial theory supports that certain sources of risk are assessed by the market. Assets with more risk may provide higher average returns. If  $\sigma_t^2$  is an appropriate measure of risk, the conditional variance may enter the conditional mean function of GARCH models (Verbeek, 2004). This estimated model is known as ARCH-in Mean or ARCH-M model and it is specified as:

$$Y_t = X_t \theta + \delta \sigma_t^2 + \varepsilon_t \tag{10}$$

where  $\theta$  is the regression coefficient.

#### 3.5.2.1. Diagnostic Testing

In this paper, three very important hypotheses are used to determine if the time series have the properties of variable variance (ARCH effect) according to Heij et al. (2004):

- (1) Residuals are white noise.
- (2) Time-varying variance (clustered volatility).
- (3) Distributions with excess kurtosis (fat tails) > 3.

Also, the test take into consideration Breusch-Pagan test where residuals  $\varepsilon_t$  have been estimated from the mean equation. Then an auxiliary regression of the squared residuals ( $\varepsilon_t^2$ ) is estimated upon the lagged squared terms ( $\varepsilon_{t-1}^2, \ldots, \varepsilon_{t-q}^2$ ) and compute  $R^2$  times *T* (Asteriou & Hall, 2007, pp. 252– 253). When the models have ARCH effect, then the Maximum Likelihood is the most appropriate estimation method in relation to least squares. The latter is an improper estimation method, because the estimations are consistent but they are also biased and inefficient. Identification of the lag selection of ARCH process can be achieved by observing the autocorrelation function of the squared residuals of the estimated model. The appropriate lag structure for the conditional variance is resulted by examination of the SACF of the squared residuals and by AIC and SIC criteria in a series of ARCH models. Also, the comparison of forecasted series with actual series from models with different lags of ARCH and GARCH terms shows that the models with the lowest SIC and AIC generate the best static ex-post forecasts. This method of ARCH specification is followed by this research. (The autocorrelations functions can be provided by the authors).

# 3.6. Combining methodology

The theory of combining forecasts is also used in order to minimize the forecasting errors. The methodology which is used in this paper is the simple average of individual forecasts of VAR or VECM, ARMA and GARCH models, a combining procedure that has been worked well in practice by Clemen (1989).<sup>4</sup> The methodology is based on the estimation of ex-post forecasts of previous individual models and then calculating the average value of these forecasts. By adopting this methodology, it is proved that the forecasting errors can be reduced in relation to forecasts of individual models.

The weighting according to average is used by Clemen (1989), Palm and Zellner (1992), Aiolfi and Timmermann (2006), and Rapach and Strauss (2008). The mathematical form of combining forecasts with simple average weight can be expressed as:

$$\mathbf{Y}_{c,t+h\setminus t} = \sum_{i=1}^{n} \mathbf{W}_{i,t} \mathbf{Y}_{i,t+h\setminus t} \tag{11}$$

where  $Y_{c,t+h\setminus t}$  is the combined forecast, w is the weight average, and  $Y_{i,t+h\setminus t}$  are the individual forecasts of models. The number of models *i* for the current research is three, (1) VAR or VECM, (2) ARMA, and (3) GARCH. More specifically, the methodology of combining forecasts in this research is referred to forecasts from each category of econometric model, one from the multivariate models (VAR or VECM—the best forecast of them), one from the univariate models with constant variance (ARMA), and one from the univariate models with time-varying variance (GARCH or EGARCH—the best forecast of two). The choice of three models is based on the occasion that models from the same category (VAR-VECM and GARCH–EGARCH) have very close forecasted values, and for this reason, the selection of one model from each category is more appropriate.

#### 4. Data

The sample period of research is based on monthly time series of 494 observations from January 1970 to February 2011. It is worth pointing out that it's the first paper which adopts such a large sample in order to examine and to compare the multivariate systems with the univariate models. Data obtained from Clarksons and especially from the Shipping Intelligent Network internet database.

The categorization of vessels is become according to their deadweight and is separated in eight types, five for tankers and three for bulk carriers. In particular, the eight categories are (Table 2):

Table 2. Categorization of vessels acco	rding to their deadweight
Tankers	Bulk carriers
1. ULCC-VLCC (200,000 dwt+)	1. Capesize (80,000 dtw+)
2. Suezmax (120,000-199,999 dwt)	2. Panamax Bulk (50,000–79,999 dwt)
3. Aframax (80,000–119,999 dwt)	3. Handymax (15,000–49,999 dwt)
4. Panamax (50,000–79,999 dwt)	
5. Handysize (18,000–35,000 dwt)	

Table 3. Examinant variables for multiple	equations models
Endogenous	
Spot rates (\$/day)	Fleet capacity (million dwt)
Timecharter rate (\$/day)	Newbuilding prices (\$ million)
Second-hand prices 5-year (\$ million)	Scrap prices (\$/ldt)
Exogenous	
Worldwide GDP	Seaborne trade (million tones)

In this research, the main shipping variables are used in multivariate systems. These variables are spot and timecharter rates, secondhand, newbuilding, scrap prices, and fleet capacity. Also, percentage change of world GDP or seaborne trade<sup>5</sup> is used as exogenous variables in VAR and VECM models (Table 3). The connection of macroeconomics with shipping variables is a usual practice in econometric interpretation of shipping phenomena and was used in several works, as Conrad, Gultekin, and Kaul (1991), Beenstock and Vergottis (1993), and Stopford (1997).

# 4.1. Forecasting procedure

Spot markets are too complicated and researchers cannot depend only on the theory of shipping economy in order to generate accurate decisions about the future values of spot prices. A methodology of forecasting spot markets is necessary as an additional tool of taking the most profitable decisions. Also, the use of forecasting is very essential to evaluate the estimated models by the comparison of forecasted and actual series (Cooper & Nelson, 1975). In other words, forecasting can be used to model specification (Xideas & Geomelos, 2011).

This paper produces point ex-post and ex-ante forecasts. Point forecasts predict a single number in each forecasting period. For ex-post forecast the last 12 observations of estimated sample are used to evaluate the estimated models, from March 2010 to February 2011. For ex-ante forecasts, the sample is extended for other 12 observations from March 2011 up to February 2012. For this time interval, the actual spot prices are unknown and could be taken from ex-ante forecasts which can be used for alternative policy decisions. Static forecasts have been used on ex-post forecasts to test validity and forecasting accuracy of the models. This can help policy-makers decide how many observations (months) can be used for forecasting.

The comparison of excluded estimations according to ex-post and ex-ante forecasts provides useful knowledge and information about the variables that affect spot markets and each vessel type. Also, shows which model depicts more accurate the future track of spot series.

The quantitative criterions, which evaluate the forecasts, are Root Mean Square Error (RMSE) and Theil's Inequality Coefficient.

# 5. Estimation results

# 5.1. Stationarity-seasonality

The results of unit root and stationarity tests are presented in Appendix, Table A1. Spot prices for all ship types are stationary in 95% confidence interval according to ADF and PP unit root tests. Also, estimations confirmed the studies of Caner and Kilian (2001) and Kuo and Tsong (2004) as KPSS test reject the hypothesis of stationarity in such a large sample of 494 observations. The results show that KPSS is satisfied only in case of ULCC. But when the sample is separated in half into two periods, (20 years in each period, 1970–1990 and 1991–2011) the KPSS test confirms the results about the rejection of null hypothesis and the acceptance of stationarity of spot prices. So, this research confirms the result that KPSS test is not an appropriate stationarity test for large samples.

Table 4. See	asonal indice	s for each mo	nth for each ve	ssel type in to	inker market	
Seasonal ind	lices					
	January	February	March	April	May	June
ULCC	.939060	.888217	.894972	.851429	.92064	1.064014
Suezmax	1.00158	.903644	.944425	.911301	.95627	1.029373
Aframax	.97613	.925980	.928886	.911263	.96454	1.045815
Panamax	.98709	.920305	.883262	.847791	.91934	1.046102
Handysize	1.01565	.984155	.978709	.906427	.93486	1.015049
	July	August	September	October	November	December
ULCC	1.03521	1.101264	1.095930	1.112983	1.05030	1.045960
Suezmax	.99753	1.023298	.978473	1.049508	1.08220	1.122382
Aframax	.99748	1.042561	1.027438	1.104286	1.01731	1.058288
Panamax	1.02038	1.124750	1.110881	1.108793	1.00778	1.023505
Handysize	.98760	1.048781	1.063103	1.059473	.96075	1.045417

In similar way, timecharter rates are stationary time-series for all vessel types except for Panamax in tanker market. As spot and timecharter prices are stationary, they haven't any trend which is confirmed by the estimations and the critical value of *F*-statistic (6.30) in Table A1.

The SACF and PACF show a sine wave for all tankers which means that they present seasonality. A characteristic correlogram of this sine wave is presented in Appendix (Figure A1) which is the same for all tankers. On the contrary, bulk carriers don't present any form of seasonality according to their correlogram (Figure A1-Capesize). The deseasonalize procedure for spot prices of tankers follows the estimation of seasonal indices which are presented in Table 4. As table shows there is higher seasonality in June and from August to December where the consumption of oil is higher for the countries of north hemisphere.

# 5.2. Multivariate models

# 5.2.1. VAR

The use of VAR-X models by the current research was adopted because there was a significant decrease of forecasting errors. The number of lags is restricted to 4 or 6 and especially in U-VLCC, Suezmax and Handysize, VAR model has 4 lags and for all other markets 6 lags. This lag structure minimizes the SIC criterion. A close relationship between the freight markets and the newbuilding market is confirmed by the estimations of models, as newbuilding prices is endogenous variable in most vessel types (except Suezmax and Aframax). The current conditions in one market affect directly the other providing important information for their development. Also, if freight market is considered as the potential income market for ship owners and the newbuilding market as the potential market of higher investments and profit then it is comprehensible why these two markets are crucial for shipping companies. A shipping company without income and new investments is mathematically clear that will be constrained and finally will leave the shipping industry. From the rest variables, fleet capacity plays a more important role in tanker market and secondhand prices in bulk carrier. More specifically, second-hand prices affect more the Panamax Bulk and Handymax markets, because in these markets exist higher sales volume according to historical data. The results of VAR models and SIC criterion are presented in Appendix Table A7.

# 5.2.2. VECM

VECM models are based on the existence of cointegration relations. The purpose of the Johansen cointegration test is to determine whether a group of non-stationary series is cointegrated or not. The numbers of lags for each vessel market are: U-VLCC 6 lags, Suezmax 4 lags, Aframax 6 lags, Panamax 4 lags, Handysize 6 lags, Capesize 6 lags, Panamax Bulk 4 lags, and Handymax 6 lags (Table A8-Appendix).

The determination of endogenous variables in VECM models has been done according to their cointegration relation to spot rates. There are five endogenous variables with at least one cointegration relation in ULCC-VLCC and Suezmax vessels. In Aframax and Panamax, there are three endogenous variables with at least two cointegration relations. In Handysize, there are also three endogenous variables with one cointegration relation. In bulk carriers, Capesize presents two endogenous variables with one cointegration relation, Panamax Bulk presents five endogenous variables with four cointegration relations, and Handymax presents three endogenous variables with three cointegration relations (Table 5).

VECM models suppose that the endogenous variables have cointegration relations analyzing at the same time the adjustment coefficients of ECM. These coefficients describe how fast the parameters are adjusted if the variables are in disequilibrium. Also, the adjustment coefficients show the trend of new adjustment (downward or upward) and the speed of this adjustment.

In both markets, tanker and bulk carrier, shipping markets are linked together with cointegration relations presenting common stochastic trend. In regard to dynamic adjustment, the larger the capacity (ULCC-VLCC=1.14%, Suezmax=5.21%, Panamax=21.85%) the slower the speed of adjustment in tanker market. This is due to that vessels with larger capacity have higher volatility which affects the speed of dynamic adjustment. In bulk carriers, Panamax Bulk has the fastest adjustment (10.14%) and Handymax the slowest (3.60%). The long-run equilibrium relations and adjustment coefficients (Dynamic Multipliers) are presented in following Table 6.

# 5.3. Univariate models

# 5.3.1. ARMA

According to Box–Jenkins methodology, AR models are of third order for Suezmax, Panamax, and Panamax Bulk. For larger capacity vessels (ULCC-VLCC, Capesize), AR models are of fifth order and for smaller capacity the order is increased (sixth order for Handysize and Handymax). So, the vessels of larger and smaller capacity seem to have higher order of AR, which is interpreted as more time lags of past values affect the current values of spot rates. Finally, Aframax market is expressed by AR(4) (Table 7).

For MA models, the orders are as follows: Suezmax and Panamax MA(2), Aframax, Handysize, and Capesize MA(3). Also, the results show MA(4), MA(5), MA(6) for ULCC-VLCC, Panamax Bulk and Handymax respectively. In conclusion, the orders of ARMA models determine the dynamic relationship of past values of spot rates from 3 to 6 months. Analytical estimations of ARMA models are presented in Appendix-Table A9.

# 5.3.2. GARCH

High volatility of spot markets means that it is necessary to examine GARCH models. According to Breusch–Pagan LM test, there is an ARCH effect for all vessel types in tanker and bulk carriers market as the variance of disturbance term is not constant but changes over time (Appendix Tables A3 and A4).

The research about the orders of ARCH and GARCH terms gives quite similar results. The best GARCH model for each vessel type is: ULCC-VLCC-GARCH-M (3,3), Suezmax-GARCH (3,3), Aframax-GARCH (4,4), Panamax-GARCH (4,4), Handysize-GARCH-M (4,4), Capesize-GARCH-M (3,3), Panamax Bulk-GARCH-M (3,3), Handymax-GARCH (1,3). For ULCC-VLCC, Handysize, Capesize and Panamax Bulk vessels, there is higher volatility as ARCH-M model is used, which means that the conditional variance is introduced into the mean equation to measure the expected risk of spot rates.

In tanker market, the largest intensity of outside shocks on spot market's volatility is in ULCC-VLCC market (1.174) and the smallest is in Suezmax market (.489). Spot rates for ULCC-VLCC present more intense response because they are affected by number of factors in relation to other vessels. For example, the vessels of large capacity are entering in fewer ports and their commercial activity is

# Table 5. Cointegration relations among endogenous variables

Johansen cointegration test				
Unrestricted cointegration rank t	est (trace)			
Hypothesized No. of CE(s)	Eigenvalue	Trace statistic	.05 Critical value	Prob.**
ULCC-VLCC: Endogenous variables:	spot, fleet, second	hand, newbuilding, scr	ар	
None*	.089433	84.16515	69.81889	.0023
At most 1	.041545	38.53912	47.85613	.2790
At most 2	.022285	17.87441	29.79707	.5754
At most 3	.010409	6.898775	15.49471	.5895
At most 4	.003695	1.802831	3.841466	.1794
Suezmax: Endogenous variables: spo	t, fleet, secondhand	l, newbuilding, scrap		
None*	.108392	89.76766	69.81889	.0006
At most 1	.042983	33.66543	47.85613	.5202
At most 2	.016981	12.18178	29.79707	.9254
At most 3	.007374	3.806977	15.49471	.9185
At most 4	.000384	.187889	3.841466	.6647
Aframax: Endogenous variables: spot	t, secondhand, fleet			
None*	.078535	56.15922	29.79707	.0000
At most 1*	.031398	16.32725	15.49471	.0374
At most 2	.001623	.791223	3.841466	.3737
Panamax: Endogenous variables: spo	ot, newbuilding, flee	t		
None*	.133653	102.1103	29.79707	.0000
At most 1*	.060149	31.95356	15.49471	.0001
At most 2	.003306	1.619169	3.841466	.2032
Handysize: Endogenous variables: sp	ot, newbuilding, scr	ар		
None*	.090231	54.63725	29.79707	.0000
At most 1	.011086	8.584316	15.49471	.4052
At most 2	.006458	3.155381	3.841466	.0757
Capesize: Endogenous variables: spot	t, newbuilding			
None*	.042562	28.31457	15.49471	.0004
At most 1*	.014540	7.133080	3.841466	.0076
Panamax Bulk: Endogenous variables	s: spot, fleet, second	lhand, newbuilding, scra	ip	
None*	.096678	129.9755	69.81889	.0000
At most 1*	.070618	80.25565	47.85613	.0000
At most 2*	.040165	44.44341	29.79707	.0005
At most 3*	.029025	24.39738	15.49471	.0018
At most 4*	.020230	9.994036	3.841466	.0016
Handymax: Endogenous variables: sp	oot, fleet, secondhai	nd, newbuilding		
None*	.072522	78.95723	47.85613	.0000
At most 1*	.045369	42.29303	29.79707	.0011
At most 2*	.023572	19.68147	15.49471	.0110
At most 3*	.016423	8.064460	3.841466	.0045

Note: Trace test indicates one cointegrating equation(s) at the .05 level.

\*Rejection of the hypothesis at the .05 level.

\*\*MacKinnon–Haug–Michelis (1999) *p*-values.

Table 6. Long-run equilibrium	relations and adjust	tment coefficients	
ULCC-VLCC			
Spot <sub>t</sub> =-1.54 Secondhand <sub>t</sub> +5.64 New	building <sub>t</sub> – 27.96 Scrap <sub>t</sub> +	+.58 Fleet <sub>t</sub> -180.48	
(3%) (.2%) (.49	%) (06%)	(.18%) = 1.149	6
Suezmax			
Spot <sub>t</sub> =+2.98 Secondhand <sub>t</sub> +.81 Newb	uilding <sub>t</sub> -30.88 Scrap <sub>t</sub> +1	.52 Fleet <sub>t</sub> -32.46	
(-4.8%) (04%) (.2%	6) (13%)	(.04%) = 5.219	6
Aframax			
Spot <sub>t</sub> =3.06 Secondhand <sub>t</sub> +26.34			
(-9.2%) (38%) Fleet (	.06%)	=9.64%	6
Panamax			
Spot <sub>t</sub> =-5.26 Fleet <sub>t</sub> +237.75			
(-21.70%) (.03%) Newbu	ilding (.12%)	= 21.85	%
Handysize			
Spot <sub>t</sub> =9.07 Newbuilding <sub>t</sub> -53.99 Scra	<sub>t</sub> +34.49		
(-14.70%) (.24%) (04	%)	=14.98	%
Capesize			
Spot <sub>t</sub> =.97 Newbuilding <sub>t</sub> -31.27			
(-2.57%) (2.26%)		=4.839	6
Panamax Bulk			
$Spot_t = 21.55 Scrap_t - 25.35$			
(-8.35%) (.33%) Secondhand	(1.08%) Newbuilding	g (.38%) = <b>10.14</b>	%
Handymax			
Spot <sub>t</sub> =-3.24 Fleet <sub>t</sub> +148.81			
(-2.01%) (.33%) Secondhand	(.4%) Newbuilding (.	86%) = 3.609	6

Note: Long-run multipliers in italics and adjustment coefficients in bold.

limited in periods of oil or economic crisis, like present crisis. Suezmax market is more flexible and it is not affected so intensely by exterior factors. One reason is the limited number of ships, which trade in relation to ULCC-VLCC (31% less number of ships, 158% less fleet capacity<sup>6</sup>). The rest three markets, Aframax (.854), Panamax (.966), and Handysize (.852) have quite the same high response in outside shocks. The memory of volatility for tankers is U-VLCC (.170), Suezmax (.596), Aframax (.283), Panamax (.052), and Handysize (.165). It is obvious that Panamax market has the smallest memory of volatility. This is linked to the fact that Panamax vessels are more flexible to adjust to market conditions (ports, cargoes, etc.) The volatility lasts less, as many factors alter the managerial conditions of this specific market. The sum of ARCH and GARCH terms, in other words GARCH process is non-stationary for all tankers (U-VLCC 1.344, Suezmax 1.085, Aframax 1.137, Panamax 1.018, and Handysize 1.017). This result is expected, as there are very sharp increase and decrease in spot rates' volatility in all markets. Spot rates' volatility of tanker market can be characterized as non-regular according to GARCH model.

In bulk carrier market, Handymax market has the largest intensity of outside shocks for the bulk carrier market (.340) and Panamax Bulk market has the smallest (.146). This result confirms the results of Jing, Marlow, and Hui (2008). The intense of outside shocks is larger in Handymax because the number of ships is double in relation to Capesize market (Fleet Number-Capesize: 1400 ships, Handymax: 2540 ships). Handymax market is characterized by flexibility and adaptability in shipping routes, ports and cargoes. GARCH coefficients for Capesize, Panamax Bulk and Handymax are .749, .861, and .708 respectively. Handymax market has the smallest memory of volatility because the intense activity of ships leads to many changes in spot rates. The respective values of Jing, Marlow, and Hui (2008) are .726, .763, and .497 where the row of numbers is confirmed by the current

#### Table 7. ARMA orders and lag operators for each vessel type

ULCC-VLCC: SARMA (5,4)

 $Spot_{t} = 50.51 + u_{t}$ 

 $(1+1.28L)(1+.57L^2)(1-.14L^3)(1-.93L^4)(1-.82L^5)(1-.70L^{12})u_t = (1+2.25L)(1+2.60L^2)(1+2.16L^3)(1+.95L^4)(1-.71L^{12})\varepsilon_t$ 

Suezmax: SARMA (3,2)

 $\text{Spot}_{t} = 84.36 + u_{t}$ 

 $(1 - .11L)(1 + .18L^2)(1 - .77L^3)u_t = (1 - .89L)(1 - .90L^2)(1 - .14L^{12})\varepsilon_t$ 

# Aframax: SARMA (4,3)

 $Spot_t = 109.74 + u_t$ 

 $(1+.83L)(1+.19L^2)(1-.61L^3)(1-.66L^4)(1-.33L^{12})u_t = (1-1.85L)(1-1.84L^2)(1-.92L^3)e_t$ 

Panamax: SARMA (3,2)

 $Spot_t = 65.13 + u_t$ 

 $(1 - .47L)(1 + .33L^2)(1 - .56L^3)(1 - .72L^{12})u_t = (1 - .59L)(1 - .60L^2)(1 + .66L^{12})\varepsilon_t$ 

Handysize: SARMA (6,3)

 $Spot_{t} = 196.08 + u_{t}$ 

 $(1 - .70L)(1 + .21L^{2})(1 + .61L^{3})(1 - .92L^{4})(1 + .20L^{5})(1 - .15L^{6})(1 - .73L^{12})u_{i} = (1 - .22L)(1 - .20L^{2})(1 - .96L^{3})(1 + .67L^{12})e_{i}$ 

# Capesize: SARMA (5,3)

 $Spot_{t} = .004 + u_{t}$ 

 $(1+.68L)(1+.86L^{2})(1+.64L^{3})(1-.10L^{4})(1+.15L^{5})(1+.77L^{12})u_{t} = (1-1.09L)(1-1.10L^{2})(1-.89L^{3})(1-.82L^{12})e_{t} = (1-1.09L)(1-.84L^{3})(1-.82L^{12})e_{t} = (1-1.09L)(1-.84L^{3})($ 

# Panamax Bulk: ARMA (3,5)

 $Spot_{t} = 2.53 + u_{t}$ 

 $(1-.67L)(1+.53L^2)(1-.71L^3)u_t = (1-.56L)(1-1.07L^2)(1-.19L^3)(1-.18L^4)(1+.22L^5)\varepsilon_t$ 

#### Handymax: ARMA (8,6)

 $Spot_{t} = -3.57 + u_{t}$ 

 $(1-.95L)(1-.40L^2)(1+.75L^3)(1-.56L^4)(1+.65L^5)(1+.28L^6)(1-.97L^7)(1+.29L^8)u_t = (1-.39L)(1+.27L^2)(1-.25L^3)(1+.26L^4)(1-.39L^5)(1-.97L^6)\varepsilon_t$ 

research. The sum of ARCH and GARCH terms is very close to unity. More specifically, the values are 1.064, 1.007, and 1.048 for Capesize, Panamax Bulk, and Handymax, respectively. GARCH processes are non-stationary and this is due to the high volatility of spot rates from 2003 until the end of the current sample (2011). Analytical estimations of GARCH models are presented in Appendix-Table A10.

#### 5.3.3. E-GARCH

In tanker market, E-GARCH models are restricted in 1 ARCH and 1 GARCH terms in ULCC-VLCC, Aframax and Panamax markets. Only Handysize has four GARCH terms. Three markets (Suezmax, Aframax, and Handysize) include conditional variance and the expected risk of return affects spot rates. The persistence of shocks to volatility is great and it is almost the same for all tankers (>.951). All tankers show asymmetry in their spot rates volatility and the positive innovations contribute more in volatility in relation to the negative innovations [ $\gamma$ =(.365 U-VLCC), (.463 Suezmax), (.327 Aframax), (.339 Panamax), and (.291 Handysize)].

In bulk carriers the models are expressed as E-GARCH-M, because the conditional variance is included in spot rates' volatility interpretation (Table 8). The intense of shocks is very limited in relation to GARCH models (Capesize .133, Panamax Bulk .212, and Handymax .210). The persistence of shocks to volatility is very close to unity and has great impact for all bulk carriers (Capesize .988, Panamax Bulk .973, and Handymax .989). Asymmetric volatility in spot rates is statistically significant and positive innovations affect more the magnitude of volatility in relation to negative innovations, as in tanker market [ $\gamma$ =(.527 Capesize), (.140 Panamax Bulk), and (.187 Handymax)]. Analytical estimations of E-GARCH are presented in Appendix-Table A11.

Table 8. GARCH a	nd E-GARCH models in bulk shipping	
		Models
Vessels	GARCH model specification	E-GARCH model specification
ULCC-VLCC	GARCH-M (3,3)	E-GARCH (1,1)
Suezmax	GARCH (3,3)	E-GARCH-M (0,1)
Aframax	GARCH (4,4)	E-GARCH-M (1,1)
Panamax	GARCH (4,4)	E-GARCH (1,1)
Handysize	GARCH-M (4,4)	E-GARCH-M (1,4)
Capesize	GARCH-M (3,3)	E-GARCH-M (1,3)
Panamax Bulk	GARCH-M (3,3)	E-GARCH-M (1,6)
Handymax	GARCH (1,3)	E-GARCH-M (1,6)

# 5.4. Ex-post forecasting results

The forecasting accuracy of VAR models is very high with very low RMSE and Theil values. This means that spot prices are affected by the interaction with other endogenous variables such as newbuilding and second-hand prices.

VECM models have very low forecasting errors and they give the best forecasts in five out of eight ship types according to Table 9. More specifically, VECM produce the best forecasts in Aframax and Panamax and in all bulk carriers. It seems that the bulk carriers are affected more by other endogenous variables and especially the second-hand and newbuilding prices and not by the past behavior of spot prices.

According to Table 9, ARMA models give better forecasting results only in case of Handysize market. Consequently, in bulk shipping the past values of spot prices cannot produce accurate forecasts and it seems that the current values of spot prices are moving independently from the past behavior of its values.

GARCH models give better forecasts in relation to other univariate models (ARMA, E-GARCH) for all vessel types (except Suezmax, Handysize). This result points out that spot prices seem to be affected more from their volatility than from their past values. This conclusion agrees with the fact that the vessels with larger capacity show larger volatility in their spot prices.

Forecasting accuracy of EGARCH models is worse in relation to GARCH models for all ship types except the Suezmax market. Also, EGARCH models seem to have better predictions compared to ARMA models.

					Mod	els				
Vessels	AR	MA	GA	RCH	EGA	RCH	VA	AR	VEC	м
	Theil	RMSE								
ULCC-VLCC	.093	9.041	.086	8.326	.087	8.467	.071	6.757	.075	7.101
Suezmax	.091	17.11	.090	17.05	.089	16.73	.101	19.32	.099	18.86
Aframax	.109	26.20	.096	23.09	.097	23.15	.089	21.45	.088	21.33
Panamax	.084	19.90	.066	17.56	.066	18.01	.061	15.76	.054	14.40
Handysize	.072	2.80	.078	22.08	.079	22.40	.091	25.84	.088	25.39
Capesize	.095	4.736	.089	4.379	.088	4.402	.055	2.734	.055	2.716
PanamaxB	.081	9.478	.078	9.145	.082	9.743	.059	6.848	.056	6.499
Handymax	.062	7.898	.048	6.060	.048	6.074	.038	4.771	.032	4.117

# Table 9. Forecasting results (ex-post static forecast)—Theil and RMSE criterions

Note: Numbers in bold show the model with the smallest forecasting errors (Read table horizontally).

Table 10. Eva	luation of ex-d	inte forecast 1	2 months—The	eil and RMSE ci	riterions			
	Models							
Criteria	U-VLCC		Suezmax		Aframax		Panamax	
	VAR	Combining forecast	E-GARCH	Combining forecast	VECM	Combining forecast	VECM	Combining forecast
Theil	.0091	.0072	.0330	.0310	.0101	.0055	.0179	.0078
RMSE	8.2419	6.5278	42.307	42.061	16.5693	8.9541	38.371	16.641
	Models							
Criteria	Handysize		Capesize		Panamax Bulk		Handymax	
	ARMA	Combining forecast	VECM	Combining forecast	VECM	Combining forecast	VECM	Combining forecast
Theil	.0253	.0267	.0199	.0162	.0293	.0288	.0176	.0158
RMSE	68.345	69.399	4.9399	4.0306	12.795	12.563	7.419	6.671

Note: Numbers in bold show the model with the smallest forecasting errors (Read table horizontally).

#### 5.5. Combining forecasts

In spot market, the methodology of combining forecasts is verified for seven out of eight vessel types. This methodology is not confirmed in case of Handysize market, where ARMA model produces the best *ex-post* forecasts in relation to combined forecasts. This confirms even more the result that spot prices in Handysize market are influenced decisively from their past values (Table 10).

#### 5.6. Ex-ante forecasting results

In this category of forecasts, the actual data are unknown and the predictions are characterized as out of-sample. These forecasts can be used by decision-makers for alternative policies in freight markets. The 12-month period for spot market is very long, but every decision-maker can determine the forecasting period to his necessities. The models of this paper can be adjusted for shorter time periods with better forecasting accuracy of future movements of spot prices.

More specifically, *ex-ante* forecasts for ULCC-VLCC market show an intense volatility for the 12-month forecasting period. For the first two months, spot prices are increased and afterward they follow a downturn track. At the end of the sample, spot prices are raised again. For Suezmax, *ex-ante* forecast is close to the mean value of spot prices and show little fluctuation. For the rest three categories of tankers (Aframax, Panamax and Handysize), *ex-ante* forecasts show an intense increase with little fluctuations after the intense volatility of *ex-post* period.

In bulk carrier market, future predictions are smoother. In Capesize market, forecasts show a stable movement with little variance. In Panamax Bulk and Handymax market, the future trend follows a downturn track with more sharp decrease in the latter market. All *ex-post* (static), *ex-ante*, and combined forecasts are depicted in the following Figures (1–4).

Static ex-post forecast depicts very accurately the actual data in U-VLCC (VAR model) and Suezmax (E-GARCH model) markets and reproducing most of the turning points after the intense increase of spot rates. Ex-ante forecast is characterized by intense fluctuations in case of U-VLCC, where VAR (green line) and combined forecasts (black line) follows very well the actual series. In Suezmax, ex-ante forecast gives a very smooth line in contrary to the sharp increase and decrease in actual data.

VECM model for both markets of Aframax and Panamax produce very accurate ex-post forecasts. It is obvious from the figure that there is a lag structure of one period between the forecasted and actual series. Also, the combined ex-ante forecasts reproduce very well the movements of actual series in the short-term period of four months outperforming the forecasts of individual forecasts of VECM models.

Figure 1. Ex-post and ex-ante forecasts for U-VLCC and Suezmax markets.



















# Figure 3. Ex-post and ex-ante forecasts for Handysize and Capesize markets.

Figure 4. Ex-post and ex-ante forecasts for PanamaxB and Handymax markets.

ARMA model's ex-post forecast for Handysize market follows the changing trends of actual data missing only the first turning point. On the contrary, VECM model in Capesize market can generate very accurate ex-post forecasts. Combined ex-ante forecasting is following the sharp increase and decrease in actual data only in case of Capesize. Handysize market is the only market where combined forecasting cannot generate forecasts with lower forecasting errors.

VECM ex-post forecasts for the last 12 observations (red line), for both Panamax Bulk and Handymax markets, is quite close to the actual data (blue line) and reproduces most the sharp decrease of actual data. Ex-ante forecasts can produce only the decreasing trend of actual series and they have a very smooth decay especially in Panamax Bulk market.

# 6. Conclusions

The extensive analysis of different econometric models and from different econometric methodologies results a number of important conclusions. First of all, spot prices for all tankers and bulk carriers are stationary confirming the classical economic theory which supports the stationarity of freight rates in a perfect competitive market. Also, tankers present seasonality and particularly in the second semester of the year as the consumption of oil is increased. The volatility of spot prices is asymmetric for both tanker and bulk carrier markets with the characteristic volatility of positive innovations to be larger than that of negative. GARCH processes are non-stationary for all ship types of tanker and bulk carrier markets confirming the result that spot prices have irregular volatility.

More specifically, in ULCC vessels, the past values of spot prices affect the present values in a period of five or six months. Spot prices are adapted more slowly in a case of disequilibrium of market presenting a higher risk. Cointegration relations prove the existence of common stochastic trend among spot, newbuilding and second-hand prices. VAR models can produce more accurate forecasts in relation to other models.

The influence of past values to current spot prices in Suezmax market is limited to a quarter of year. The univariate models and especially the examination of volatility according to E-GARCH models give the best *ex-post* forecasts in relation to multivariate models.

In Aframax market, the effect of past values concerns a four-month period and in Panamax concerns a quarter. Forecasting evaluation shows that VECM models and especially the close relation between spot and second-hand prices for Aframax and spot and newbuilding prices for Panamax simulates the actual spot prices more precisely in relation to all examinant models.

ARMA model plays a decisive role in the formation of Handysize spot prices. Firstly, past behavior of spot prices affects current prices in a period of six-month and produces more accurate forecasts.

In bulk carriers, the influence of past values of spot price concerns five-month, three-month, and four-month lags for Capesize, Panamax Bulk, and Handymax, respectively. Also, VECM model produces more accurate forecasts for all three categories of ships showing homogeneity in the forecasting procedure indicating that the spot prices are affected from other endogenous variables and not only from the past values of spot rates.

Finally, the combining methodology of previous univariate and multivariate models provide lower forecasting errors in seven out of eight categories (except Handysize) of ships using the simple average of forecasts instead of the forecasts of each individual model. A future research can compare more econometric models such as simultaneous equations models or multiple regressions and can use more complicate combining methods in order to minimize, as possible, the forecasting errors in spot markets.

#### Acknowledgment

The authors wish to thank two anonymous referees for their useful comments and their constructive suggestions.

#### Author details

N.D. Geomelos<sup>1</sup>

E-mail: n.geomelos@chios.aegean.gr

E. Xideas<sup>1</sup>

E-mail: exideas@aegean.gr

<sup>1</sup> Department of Shipping, Trade and Transport, University of the Aegean, G. Veriti 84, Chios 82100, Greece.

#### Article Information

Cite this article as: Forecasting spot prices in bulk shipping using multivariate and univariate models, N.D. Geomelos & E. Xideas, Cogent Economics & Finance (2014), 2: 932701.

#### Cover image

Source: Author

#### Notes

- 1. A unit root process is a highly persistent time series process where the current value equals last period's value, plus a weakly dependent disturbance (Wooldridge, 2002).
- 2. The method of estimation of seasonal indices is referred in detail in Pindyck and Rubinfeld (1998, pp. 482–484).
- 3. As Sims (1980) noticed, the specification of some of variables as exogenous introduces restrictions on the model, because they affect the endogenous variables directly through feedback procedure.
- 4. For the advantages of simple average, see the paper of Palm and Zellner (1992, pp. 699-700).
- 5. In VAR and VECM models, it is used only one variable of them (GDP [%] or seaborne trade [%]) in order to avoid any correlation problems.
- 6. Authors estimations based on Clarksons SIN database.

#### References

Aiolfi, M., & Timmermann, A. (2006). Persistence in forecasting performance and conditional combination strategies. Journal of Econometrics, 135, 31-53. http://dx.doi.org/10.1016/j.jeconom.2005.07.015

Asteriou, D., & Hall, S. (2007). Applied econometrics. New York, NY: Palgrave MacMillan.

Batchelor, R., Alizadeh, A., & Visvikis, I. (2007). Forecasting spot and forward prices in the international freight market. International Journal of Forecasting, 23, 101-114. http://dx.doi.org/10.1016/j.ijforecast.2006.07.004

Beenstock, M., & Vergottis, A. (1993). Econometric modelling of world shipping. London: Chapman and Hall.

Boero, G. (1990). Comparing ex-ante forecasts from a SEM and VAR model: An application to the Italian economy. Journal of Forecasting, 9, 13-24.

# http://dx.doi.org/10.1002/(ISSN)1099-131X

- Box, G. E. P., & Jenkins, G. M. (1976). Time series analysis: Forecasting and control (Revised ed.). San Francisco, CA: Holden-Day.
- Caner, M., & Kilian, L. (2001). Size distortions of tests of the null hypothesis of stationarity: Evidence and implications for the PPP debate. Journal of International Money and Finance, 20, 639-657.

http://dx.doi.org/10.1016/S0261-5606(01)00011-0

- Clemen, R. T. (1989). Combining forecasts: A review and annotated bibliography. International Journal of Forecasting, 5, 559–583.
  - http://dx.doi.org/10.1016/0169-2070(89)90012-5
- Conrad, J., Gultekin, M., & Kaul, G. (1991). Asymmetric predictability of conditional variances. Review of Financial Studies, 4, 597-622.
  - http://dx.doi.org/10.1093/rfs/4.4.597

- Cooper, J. P., & Nelson, C. R. (1975). The ex-ante prediction performance of the St. Louis and FRB-MIT-PENN econometric models and some results on composite predictors. Journal of Money, Credit and Banking, 7, 1-32. http://dx.doi.org/10.2307/1991250
- Cullinane, K. (1992). A short-term adaptive forecasting model for BIFFEX speculation, a Box-Jenkins approach. Maritime Policy and Management, 19, 1-114.
- Cuthbertson, K., Hall, S., & Taylor, M. (1992). Applied econometric techniques. London: Harvester Wheatsheaf.
- Davidson, R., & MacKinnon, G. J. (1993). Estimation and inference in econometrics. Oxford: Oxford University Press.
- Hausman, J. (1983). Specification and estimation of simultaneous equations models. Handbook of Econometrics, 1, 391-448.
  - http://dx.doi.org/10.1016/S1573-4412(83)01011-9
- Hawdon, D. (1978). Tanker freight rates in the short and long run. Applied Economics, 10, 203-218. http://dx.doi.org/10.1080/758527274
- Heij, C., De Boer, P., Franses, P., Kloek, T., & Van Dijk, H. (2004). Econometric methods with application in business and economics. New York. NY: Oxford University Press.
- Jing, L., Marlow, P., & Hui, W. (2008). An analysis of freight rate volatility in dry bulk shipping markets. Maritime Policy & Management, 35, 237-251.
- http://dx.doi.org/10.1080/03088830802079987 Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. Econometrica, 59, 1551-1580.
- http://dx.doi.org/10.2307/2938278 Kavussanos, M. G., & Nomikos, N. (1999). The forward pricing function of the shipping freight futures market. Journal of Futures Markets, 19, 353-376.

http://dx.doi.org/10.1002/(ISSN)1096-9934

- Kavussanos, M. G., & Visvikis, I. (2004). Market interactions in returns and volatilities between spot and forward shipping freight markets. Journal of Banking & Finance, 28, 2015-2049.
- http://dx.doi.org/10.1016/j.jbankfin.2003.07.004 Kilian, L. (2001). Impulse response analysis in vector autoregressions with unknown lag order. Journal of Forecasting, 20, 161–179.
- http://dx.doi.org/10.1002/(ISSN)1099-131X Kuo, B. S., & Tsong, C. C. (2004). Bootstrap inference for
- stationarity. Manuscript National Chengchi University. Litterman, R. (1984). Forecasting and policy analysis with Bayesian vector autoregression models. Federal
- Reserve Bank of Minneapolis Quarterly Review, 8, 30-41.
- Lutkepohl, H., & Kratzig, M. (2004). Applied time series econometrics. New York, NY: Cambridge University Press. http://dx.doi.org/10.1017/CBO9780511606885
- Lyridis, D. V., Zacharioudakis, P. G., Mitrou, P., & Mylonas, A. (2004). Forecasting tanker market using artificial neural networks. Maritime Economics and Logistics, 6, 93-108. http://dx.doi.org/10.1057/palgrave.mel.9100097
- Newbold, P. (1983). ARIMA model building and the time series analysis approach to forecasting. Journal of Forecasting, 2, 23-35. http://dx.doi.org/10.1002/(ISSN)1099-131X
- Palm, F., & Zellner, A. (1992). To combine or not to combine? Issues of combining forecasts. Journal of Forecasting, 11,687-701
- http://dx.doi.org/10.1002/(ISSN)1099-131X Perron, P. (1989). The great crash, the oil price shock, and the unit root hypothesis. Econometrica, 57, 1361-1401. http://dx.doi.org/10.2307/1913712
- Pindyck, R., & Rubinfeld, D. (1998). Econometric models and economic forecasts. Boston, MA: Irwin McGraw-Hill.
- Randers, J., & Göluke, U. (2007). Forecasting turning points in shipping freight rates: Lessons from 30 years of practical effort. System Dynamics Review, 23, 253-284. http://dx.doi.org/10.1002/(ISSN)1099-1727

Rapach, D., & Strauss, J. (2008). Forecasting US employment growth using forecast combining methods. *Journal of Forecasting*, 27, 75–93.

http://dx.doi.org/10.1002/(ISSN)1099-131X

- Scarsi, R. (2007). The bulk shipping business: Market cycles and shipowners' biases. Maritime Policy & Management, 34, 577–590. http://dx.doi.org/10.1080/03088830701695305
- Sims, C. (1980). Macroeconomics and reality. *Econometrica*, 48, 1–47. http://dx.doi.org/10.2307/1912017
- Stopford, M. (1997). Maritime economics. London: Routledge. http://dx.doi.org/10.4324/9780203442661
- Tsolakis, S. (2005). Econometric analysis of bulk shipping markets, implications for investment strategies and financial decision making (PhD diss.). Erasmus University, Rotterdam.

UNCTAD-Review of Maritime Transport. (2011). Chap. 1, pp. 1–33. Veenstra, A., & Franses, P. (1997). Multivariate autoregressive models for forecasting seaborne trade flows. *Transportation Research Part E*, 37, 311–319.

Verbeek, M. (2004). A guide to modern econometrics. Chichester: John Wiley & Sons.

Wooldridge, J. (2002). Introductory econometrics: A modern approach. New York, NY: South-Western College.

Xideas, E., & Geomelos, N. D. (2011). An empirical investigation of spot prices in tanker market using dynamic multiple regression models. *International Journal of Decision Sciences, Risk and Management,* 3, 238–259. http://dx.doi.org/10.1504/IJDSRM.2011.046153

# Appendix

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob	Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
·		1	0.848	0.848	357.49	0.000	-		1	0.968	0.968	466.04	0.000
	Q+	2	0.698	-0.075	600.39	0.000		· ·	2	0.914	-0.376	882.35	0.000
·	p	3	0.593	0.072	776.02	0.000		i pi	3	0.860	0.111	1251.5	0.000
·	( )) (	4	0.514	0.025	908.00	0.000		i)D	4	0.814	0.073	1583.1	0.000
· —	יום	5	0.401	-0.154	988.72	0.000		<b> </b>	5	0.783	0.158	1890.6	0.000
· 🗖 ·	ייףי	6	0.322	0.065	1040.7	0.000		<b>[</b> ]	6	0.756	-0.107	2177.9	0.000
· 🗖 ·	' <b> </b>	7	0.306	0.151	1087.7	0.000			7	0.729	0.009	2445.0	0.000
· 🗖 ·	1	8	0.294	-0.003	1131.3	0.000		i)D	8	0.703	0.076	2694.3	0.000
·Þ	( )) (	9	0.271	0.016	1168.3	0.000		վի	9	0.681	0.037	2928.5	0.000
· 🗖 ·		10	0.252	0.013	1200.5	0.000			10	0.647	-0.305	3140.2	0.000
· 🗖 ·	i   i	11	0.278	0.123	1239.6	0.000	·		11	0.610	0.149	3328.7	0.000
· 🗖 ·	i pi i	12	0.307	0.068	1287.6	0.000	·	ի	12	0.577	0.057	3497.7	0.000
· 🗖 ·	· 🗖 ·	13	0.245	-0.255	1318.3	0.000		i)D	13	0.551	0.067	3652.5	0.000
- <b>-</b>	)U	14	0.187	0.023	1336.3	0.000	· 💻		14	0.536	-0.047	3799.4	0.000
- In the second se		15	0.149	-0.026	1347.6	0.000	· 🚞	վի	15	0.524	0.028	3939.7	0.000
i 🗖 i		16	0.120	-0.010	1355.0	0.000	· 📩	d i	16	0.504	-0.103	4069.7	0.000
ı þi	l iþi	17	0.082	0.061	1358.5	0.000			17	0.484	0.159	4190.1	0.000
ı þ	)i	18	0.066	0.022	1360.7	0.000	· 📩	i i i i i i i i i i i i i i i i i i i	18	0.477	0.130	4307.1	0.000
ı þ	)i	19	0.083	0.022	1364.3	0.000	· 📩		19	0.469	-0.151	4420.5	0.000
i 🗖 i	i pi	20	0.115	0.095	1371.1	0.000	· 🗖	i bi	20	0.463	0.081	4531.2	0.000
· 🖻	)i	21	0.138	0.014	1381.1	0.000	· 📩	1	21	0.456	0.007	4638.9	0.000
· 🗖	i pi	22	0.168	0.079	1395.8	0.000	·	1	22	0.445	0.005	4741.9	0.000
· 🗖 ·	1	23	0.207	0.007	1418.0	0.000	·	1	23	0.440	0.005	4842.6	0.000
· 🗖 ·	1	24	0.237	0.004	1447.3	0.000	· 📩	վի	24	0.438	0.039	4942.7	0.000
· 🗖	( ()	25	0.205	-0.084	1469.3	0.000	· 📩	uli –	25	0.432	-0.045	5040.0	0.000
· 🗖 ·	() ()	26	0.157	-0.059	1482.3	0.000	· 📩	- du	26	0.422	0.015	5133.1	0.000
· b	l (p	27	0.142	0.093	1492.9	0.000		10	27	0.417	0.060	5224.4	0.000
1	ի ի	28	0.143	0.054	1503.7	0.000	· 📩	- united and a second sec	28	0.415	0.026	5315.1	0.000
i la	- du	29	0.135	0.016	1513.2	0.000		- fi	29	0.419	0.032	5407.7	0.000
- la	ի ի	30	0.136	0.047	1523.0	0.000	ı 🔚	ան	30	0.422	-0.030	5501.9	0.000
· 🗖 ·	ի ին	31	0.167	0.036	1537.8	0.000	1	l li	31	0.418	0.002	5594.3	0.000
· 🗖	ի	32	0.212	0.063	1561.6	0.000		ali i	32	0.410	-0.026	5683.7	0.000
· 🗖 ·	l iji	33	0.234	0.008	1590.6	0.000		i i	33	0.404	-0.005	5770.5	0.000
		34	0.272	0.101	1630.0	0.000		i bi	34	0.399	0.072	5855.3	0.000
	10	35	0.311	0.013	1681.7	0.000		ան	35	0.390	-0.090	5936.7	0.000
· 🗖		36	0.367	0.127	1753.6	0.000		- Di	36	0.384	0.047	6015.6	0.000
· 🖿		37	0.341	-0.122	1816.0	0.000	-	16	37	0.378	0.036	6092.0	0.000
· 🗖	i i	38	0.296	-0.002	1863.1	0.000	· 🚍	d,	38	0.372	-0.084	6166.4	0.000

Figure A1. Correlograms of ULCC-VLCC and Capesize.

-
Ś
10
<b>U</b>
<b>A</b>
<u> </u>
<u> </u>
- <b>П</b> .
4
$\sim$
<b>U</b>
<u> </u>
<u> </u>
_
•
- 0
~
_
- ×
_
- <b>-</b>
41
- <b>-</b>
_ <u>~</u>
•
10
++
st
est
test
test
y test
ty test
ity test
rity test
arity test
arity test
narity test
pnarity test
ionarity test
tionarity test
ationarity test
ationarity test
tationarity test
stationarity test
stationarity test
d stationarity test
nd stationarity test
nd stationarity test
and stationarity test
and stationarity test
t and stationarity test
pt and stationarity test
pot and stationarity test
oot and stationarity test
root and stationarity test
: root and stationarity test
it root and stationarity test
nit root and stationarity test
init root and stationarity test
unit root and stationarity test
f unit root and stationarity test
of unit root and stationarity test
of unit root and stationarity test
of unit root and stationarity test
s of unit root and stationarity test
ts of unit root and stationarity test
lts of unit root and stationarity test
ults of unit root and stationarity test
sults of unit root and stationarity test
sults of unit root and stationarity test
esults of unit root and stationarity test
results of unit root and stationarity test
results of unit root and stationarity test
t results of unit root and stationarity test
st results of unit root and stationarity test
est results of unit root and stationarity test
Test results of unit root and stationarity test
Test results of unit root and stationarity test
. Test results of unit root and stationarity test
1. Test results of unit root and stationarity test
<b>A1. Test results of unit root and stationarity test</b>
A1. Test results of unit root and stationarity test

Tankers

**Table** 

					Unit	root tests						
Ships variables	Un (con	it root t( stant)—	est ADF	Unit root te tre	est (cons nd)—AD	stant and F	Unit root (constant)	test P	Unit root test (cor and trend)—F	nstant PP	KPSS	
Shipping variables	Constant	Lags	F-statistic	Constant and trend	Lags	F-statistic	Intercept	Lags	Intercept and Trend	Lags	Intercept	Lags
NTCC-NTCC												
SPOT	-4.349763	14	7.15	-4.485632	15	.63	-6.517016	1	-6.535936	1	.378429	15
LogSPOT	-5.041852	1	5.69	-5.271801	1	1.13	-5.143787	1	-5.383386	1	.682676	16
Timecharter_Rate	-4.299262	14	6.79	-4.372307	15	.33	-5.550506	m	-5.554937	m	.326355	16
LogTimecharter_Rate	-3.400368	12	5.55	-3.556815	12	.59	-3.524808	c	-3.614347	m	.537454	17
Suezmax												
SPOT	-5.422573	2	9.98	-5.977616	m	3.04	-5.363671	2	-5.948075	2	.681236	30
LogSPOT	-4.029574	1	7.81	-4.810390	7	3.41	-3.681763	9	-4.582409	ß	.776276	30
Timecharter_Rate	-3.195757	14	4.03	-3.812497	15	2.19	-4.292573	m	-4.922830	2	.654286	30
LogTimecharter_Rate	-2.992747	7	4.10	-4.038741	7	3.85	-2.969223	1	-3.703819	1	.781599	30
Aframax												
SPOT	-3.411202	14	5.00	-4.211207	15	3.07	-5.723804	C	-6.394461	c	.676344	36
LogSPOT	-3.084485	12	4.87	-4.077137	12	3.59	-4.896591	S	-5.879056	4	.796458	36
Timecharter_Rate	-3.341314	14	4.90	-3.980898	15	2.37	-4.823215	2	-5.346847	2	.708642	30
LogTimecharter_Rate	-3.138246	12	4.97	-3.900330	12	2.72	-3.561784	Э	-4.300588	4	.811075	30
Panamax												
SPOT	-3.835933	8	6.26	-4.599261	6	3.18	-5.877790	5	-6.637076	4	.880332	30
LogSPOT	-3.183863	12	5.26	-4.072439	12	3.31	-5.786194	1	-6.704936	1	.945241	30
Timecharter_Rate	-2.413106	З	2.33	<b>-</b> 2.962882	4	1.67	-2.381216	5	-2.903565	5	1.114308	30
Log Timecharter_Rate	-3.648740	12	7.24	-4.617425	12	4.76	-3.210518	5	-4.564920	1	1.151128	30
Handysize												
SPOT	-4.841871	4	10.03	-5.426465	5	2.95	-5.746835	4	-6.563017	5	.814924	30
LogSPOT	-2.954724	12	4.57	-3.373456	12	1.52	-5.410445	4	-6.301460	5	.862364	30
Timecharter_Rate	-3.421291	15	5.16	-4.057274	16	2.41	-4.989460	13	-5.020977	13	.333838	20
LogTimecharter_Rate	-3.323653	13	5.49	-4.256773	13	3.63	-3.307321	8	-3.744474	8	.676813	20

Table A1. (C	ontinued)														
Ignkers															
							Unit root	tests			-				
Ships variab	les	(con	it root t stant)—	est -ADF	Unit r	oot test trend)	(constant —ADF	: and	Unit re (consto	oot test int)—PP	Unit root and t	test (cons rend)—PP	stant	KP	SS
Shipping va	iables	Constant	Lags	F-statistic	: Constc and tre	ant Lo and	ags F-ste	atistic	Interce	ot Lags	Intercep	t and d	Lags	Intercep	t Lags
Critical values <i>F</i>	-statistic	_		4.61	Critic F-5	cal values statistic		5.30							_
MacKinnon critı	ical values						-	-		_	_	_			
Critical values 1	%		m <sup>i</sup>	443719		-3.97	'7251		-3.4.	43388	-	.976781		.739	000
Critical values 5	2%		-2.	867329		-3.41	9191		-2.8	67183		.418962		.463	000
Critical values 1	:0%		-2	569916		-3.13	12165		-2.5	69837		.132030		.347	000
Bulk carriers															
Shipping variables	Constant		sóp	F- C sta- 1 tistic	onst./ trend	Lags	F-statistic	Interc	cept	Lags	Interc./trend	Lags	Inte	erc./trend	Lags
Capesize															
SPOT	-3.009398		12	2.83 <b>-3.</b>	934291	13	3.24	-3.018	3661	15	-3.806438	14	· ·	191327	30
LogSpot	-2.372179		2	2.70 <b>-3.</b>	625905	2	3.25	-2.538	3752	9	-3.699099	7	••	135861	18
Timechar- ter_Rate	-3.569842		m	3.88 <b>-4.</b>	682310	12	29.44	-3.215	5520	D	-3.603720	Ū	•:	109682	16
Log- Timechar- ter_Rate	-2.95191		1	3.96 -3.	505408		1.80	-3.024	+795	10	-3.483413	10	•	048695	17
Panamax- Bulk															
SPOT	-3.106391		7	3.51 <b>-4.</b>	946269	∞	1.37	-2.909	3847	1	-3.819363	1	· :	204703	30
Log Spot	-2.574215		4	3.12 <b>-3</b> .	991097	2	1.65	-2.481	1196	3	-3.808061	4	••	111303	18
Timechar- ter Rate	-4.049112		4	4.72 <b>-4.</b>	712969	ы	2.86	-3.381	1721	Ţ	-3.837920		•:	117621	16
Log- Timechar- ter_Rate	-3.215271		1	4.83 <b>-4</b> .	349858	-	4.22	-3.050	0105	7	-3.959188	×		057740	16
Handymax															;
SPOT	-2.951275		-1	2.78 -4.	139906	-	4.19	-2.567	7013	m	-3.586628	m		215300	35
LogSpot Bulk	-2.055832		1	2.21 – <b>3</b> .	602905	-	4.44	-2.081	1199	7	-3.410146	2	· .	173846	17
Timechar- ter Rate	-3.696674		11	4.20 <b>-4.</b>	883746	12	5.07	-3.027	7410	Ŋ	-3.738123	Ω	·	160589	30
															(Continued)

**Bulk Carriers** 

							Uni	t root tests							
Ships variable	se	Cor (cor	nit root 1 1stant)–	test -ADF	<b>&gt;</b>	nit root t( tre	est (con nd)—AI	istant and DF	Unit (con:	t root test stant)—PF	, L	it root test (	constant —PP	KPS	S
Shipping vari	ables	Constant	Lags	F-statis	stic	onst./ trend	Lags	F-statistic	: Inter	cept La	gs I	nterc./trend	Lags	Interc./ trend trend	Lags
Log- Timechar- ter_Rate	-2.884710			4.68	-4.60512(	6		4.98 -2	.563987	6	-3.7	37337	6	.077196	17
Critical values F-:	statistic			4.61	Critical va	lues F-statis	stic	6.30						Kwiatkowski-Philip Shin (199	s-Schmidt-
MacKinnon critic	al values														<i>c</i> )
Critical values 19	%		-3.44371	61		-3.9772	51		-3.443	3388		-3.976781		.21600	
Critical values 5%	9		-2.86732	29		-3.4191	91		-2.867	7183		-3.418962		.14600	
Critical values 1C	%		-2.56991	16		-3.1321(	65		-2.565	9837		-3.132030		.11900	
Notes: Numbers	in hold show th	he stationarity	v in 95% r	onfidence.	interval										

Notes: Numbers in bold show the stationarity in 95% confidence interval.

Lags for ADF are estimated according to SIC criterion Lags for PP and KPSS are estimated according to Newey-West bandwidth.

Table A2. Endogenous an	d exogenous v	variables for e	ach vessel type	e in bulk shipp	ing
			Tankers		
			Vessels		
Variables	ULCC	Suezmax	Aframax	Panamax	Handysize
Spot	Endogenous	Endogenous	Endogenous	Endogenous	Endogenous
Timecharter	Exogenous	Exogenous	Exogenous	Exogenous	Exogenous
Secondhand Pr.	Endogenous	Endogenous	Endogenous	Exogenous	Exogenous
Newbuilding Pr.	Endogenous	Endogenous	Exogenous	Endogenous	Endogenous
Scrap value	Endogenous	Endogenous	Exogenous	Exogenous	Endogenous
Fleet capacity	Endogenous	Endogenous	Endogenous	Endogenous	Exogenous
% Change of GDP	Exogenous	Exogenous	Exogenous	-	-
% Change of seaborne trade	-	-	-	Exogenous	Exogenous
			Bulk carriers		
	Capesize		Panamax Bulk		Handymax
Spot	Endogenous		Endogenous		Endogenous
Timecharter	Exogenous		Exogenous		Exogenous
Secondhand Pr.	Exogenous		Endogenous		Endogenous
Newbuilding Pr.	Endogenous		Endogenous		Endogenous
Scrap value	Exogenous		Endogenous		Exogenous
Fleet capacity	Exogenous		Endogenous		Endogenous
% Change of GDP	-		-		-
% Change of seaborne trade	Exogenous		Exogenous		Exogenous

# Table A3. Estimation of ARCH effect (Tankers)

# Dependent variable: DESEASON\_SPOT

# Method: Least squares-sample (adjusted): 1970M02 2011M02

Included observations: 493 after adjustments-convergence achieved after three iterations

		-	-							
	ULCC-VLC	C	Suezma	ĸ	Aframax	ĸ	Panama	x	Handys	size
Variable	С	AR(1)	С	AR(1)	С	AR(1)	С	AR(1)	С	AR(1)
Coefficient	55.69	.862	83.80	.900	111.11	.881	149.10	.883	190.14	.8718
Std. Error	6.646	.022	10.45	.019	10.779	10.30	12.92	.021	14.797	12.849
t-Statistic	8.378	37.78	8.018	46.67	.0212	41.39	11.53	41.76	.0220	39.488
Prob.	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000	.0000

ARCH effect

Lags	X <sup>2</sup> -statistic	ULCC-VLCC	Suezmax	Aframax	Panamax	Handysize
	(critical value)			$T \times R^2$		
1	3.84	3.45	9.90	3.45	1.95	.47
2	5.99	17.58	28.98	21.14	21.90	14.87
3	7.81	41.69	43.70	28.58	24.23	19.38
4	9.49	41.68	44.12	29.15	24.24	19.91
5	11.07	57.40	52.88	38.55	35.31	29.02
6	12.59	59.54	53.13	40.18	37.30	31.59

# Table A4. Estimation of ARCH effect (Bulk carriers)

# Dependent variable: SPOT\_BULK

#### Method: Least squares-sample (adjusted): 1970M02 2011M02

#### Included observations: 493 after adjustments-convergence achieved after three iterations

	Capesize		Panamax Bull	ĸ	Handymax	
Variable	С	AR(1)	С	AR(1)	С	AR(1)
Coeffi- cient	14.28	.968	28.63	.971	28.55	.983
Std. Error	4.799	.011	7.804	.010	11.54	.008
<b>t</b> -statistic	2.977	86.69	3.669	91.91	2.473	116.3
Prob.	.0031	.0000	.0003	.0000	.0137	.0000

ARCH effect

Lags	X <sup>2</sup> -statistic (criti-	Capesize	Panamax Bulk	Handymax
	cal value)		<b>T</b> × <b>R</b> <sup>2</sup>	
1	3.84	88.98	127.99	70.96
2	5.99	89.57	127.99	72.23
3	7.81	97.15	160.50	74.43
4	9.49	206.12	175.20	89.77
5	11.07	205.75	175.44	99.52
6	12.59	206.49	178.13	102.91

Table A5. Diagnosti	c tests ARMA mo	del—Tankers		
Vessel size	Q-Stati	stic	Breusch–Godfrey LM tes	st
Tankers	<b>Q</b> <sub>LB</sub> (36)	<b>X</b> <sup>2</sup>	Serial correlation (2 lags)	<b>X</b> <sup>2</sup>
ULCC-VLCC	29.97	50.99	.71	5.99
Suezmax	39.65	50.99	2.69	5.99
Aframax	30.32	50.99	3.44	5.99
Panamax	42.56	50.99	1.69	5.99
Handysize	35.28	50.99	.03	5.99

Table A6. Diagnostic	tests ARMA mod	lel—Bulk carr	iers	
Bulk carriers	Q <sub>LB</sub> (36)	<b>X</b> <sup>2</sup>	Serial correlation (2 lags)	<b>X</b> <sup>2</sup>
Capesize	57.47	50.99	2.19	5.99
Panamax Bulk	60.39	50.99	7.50	5.99
Handymax	65.14	50.99	1.00	5.99

D(Fleet\_Dwt(-2))

-7.7321

[-1.794]

Table A7. VAR estim	nations (Tar	nker—Bulk carrie	ers)				
Vector autoregression	estimates f	or D(SPOT) ULCC-V	LCC (Tank	ers)			
Sample (adjusted): 19	70M06 2011	M02—Included ob	servation	s: 489 after adj	ustme	nts	
Variables	Coeff.	t-Statistic	v	ariables	(	Coeff.	t-Statistic
D(SPOT(-1))	0522	[-2.452]	D(Seco	ndhand_Pr.(-3))	-	3579	[-1.653]
D(SPOT(-2))	0498	[-2.344]	D(Seco	ndhand_Pr.(-4))		.0913	[.424]
D(SPOT(-3))	0008	[039]	D(Scr	ap_Value(-1))		.2268	[.274]
D(SPOT(-4))	0410	[-1.888]	D(Scr	ap_Value(-2))	2	2.6092	[3.052]
D(Newbuilding_Pr.(-1))	.3316	[1.208]	D(Scr	ap_Value(-3))	2	2.6489	[3.079]
D(Newbuilding_Pr.(-2))	.1248	[.463]	D(Scr	ap_Value(-4))	-	1.6244	[-1.915]
D(Newbuilding_Pr.(-3))	2546	[950]		С	-	3343	[589]
D(Newbuilding_Pr.(-4))	2235	[857]	Perc	entage_Gdp		.9234	[1.865]
D(Secondhand_Pr.(-1))	6511	[-3.066]	D(	Fleet_Dwt)	-	1700	[395]
D(Secondhand_Pr.(-2))	4834	[-2.212]	D(Time	echarter_Rate)	3	3.2070	[41.46]
<b>R</b> <sup>2</sup>		.798381	Ak	aike information	criteri	on	18.348
S.E. equation		10.60739		Schwarz criter	rion		19.034
Log likelihood		-4406.19					
Vector autoregression	estimates o	f D(SPOT) SUEZMA	X (Tankers	s)			
Sample (adjusted): 19	70M06 2011	M02—Included ob	servation	s: 489 after adj	ustme	nts	
Variables	Coeff.	t-Statisti	ic	Variable	5	Coeff.	t-Statistic
D(SPOT(-1))	1166	[-3.776]		D(Scrap_Value	(-3))	4.4420	[2.598]
D(SPOT(-2))	0699	[-2.259]		D(Scrap_Value	(-4))	7684	[454]
D(SPOT(-3))	0366	[-1.167]		D(Fleet_Dwt(-	-1))	6.7747	[2.260]
D(SPOT(-4))	0607	[-1.920]		D(Fleet_Dwt(-	-2))	.7851	[.267]
D(Secondhand_Pr.(-1))	-1.2100	-2.480]		D(Fleet_Dwt(-	-3))	-1.0906	[371]
D(Secondhand_Pr.(-2))	-1.2898	[-2.671]		D(Fleet_Dwt(-	-4))	-7.0020	[-2.327]
D(Secondhand_Pr.(-3))	3355	[-2.6/1]		С		8035	[866]
D(Secondhand_Pr.(-4))	.7383	[1.561]		D(Timecharter)		4.9022	[24.32]
D(Scrap_Value(-1))	3.6943	[2.209]		D(Newbuilding_Pr.)		.6445	[1.014]
D(Scrap_Value(-2))	3.5168	[2.106]		Percentage_Gdp		1.3652	[1.790]
<b>R</b> <sup>2</sup>	.5920	Akaike information	n criterion	13.74413			
S.E. equation	16.370	Schwarz crite	erion	14.43000			
Log likelihood	-3280.4						
Vector autoregression	estimates o	f D(SPOT) AFRAMA	X (Tanker	s)			
Sample (adjusted): 19	70M08 2011	M02—Included ob	servation	s: 487 after adj	ustme	nts	
Variables	Coeff.	t-Statistic	Va	riables	Co	oeff.	t-Statistic
D(SPOT(-1))	0978	[-3.104]	D(Flee	et_Dwt(-4))	6.8	8323	[1.621]
D(SPOT(-2))	0925	[-3.029]	D(Flee	et_Dwt(-5))	-6.	.6016	[-1.532]
D(SPOT(-3))	0822	[-2.613]	D(Flee	et_Dwt(-6))	-1.	.7867	[413]
D(SPOT(-4))	0765	[-2.477]		С	(	5412	[498]
D(SPOT(-5))	0319	[-1.042]	D(Timed	charter_Rate)	7.	1652	[22.26]
D(SPOT(-6))	0703	[-2.247]	D(Seco	ndhand_Pr.)	.1	497	[.208]
D(Fleet_Dwt(-1))	5.1680	[1.234]	D(New	building_Pr.)	2.	5377	[2.913]

(Continued)

[.592]

1.6467

D(Scrap\_Value)

Vector autoregression to the standing of the stan	Table A7. (Continue	ed)				
Sample (adjusted): 197000 20.882         L-Statistic         Variables         Coeff.         t-Statistic           D(Fleet_Dwt(-3))         2.8582         [.663]         Percentage_Gdp         1.0135         [.0.82]           R <sup>1</sup> 5.839         Akoike intro         8.72         [.0.82]           Lag likelihood         -2087.5         5.839         Akoike intro         8.72         [.0.82]           Vector autoregression 20185           Vector autoregression 20180         Vector autoregression 20180           Vector autoregression 20180           Vector autoregression 20180         Vector autoregression 20180           Vector autoregression 20180           Vector autoregression 20180         Vector autoregression 20180           Operation 20180           Vector autoregression 20180         Vector autoregression 20180           Operation 201800         Vector 201800           Vector autoregression 201800	Vector autoregression	n <mark>estimates of</mark> [	O(SPOT) AFRAMA	X (Tankers)		
VariablesCoeff.t-StatisticVariablesCoeff.t-StatisticD(Fleet_Dwt(-3))2.8582(.663)Percentage_6dp1.0135(1.082)R <sup>2</sup> .5839Akakeriserise in criterion8.72U14SE. equation20.185S9.03U14Leg likelihood-2087.59.03U14Leg likelihood-2087.5V9.03U14Vector autoregression voltation criterion8.72U14VariablesCoeff.t-StatisticVariablesCoeff.t-StatisticD(SPOT(-1))-0.50619[-1.278]D(Newbuilding_Pr.(-5)-1.010416[-5.671]D(SPOT(-2))-0.50819[-2.151]D(Newbuilding_Pr.(-5)-1.010416[-1.051]D(SPOT(-3))-0.33357[-2.151]D(Newbuilding_Pr.(-5)-1.010416[-1.051]D(SPOT(-6))-0.202798[-5.287]D(Timecharte_Rote)15.05347[11.93]D(Newbuilding_Pr.(-1)-1.806370[-1.033]D(Scord_Nout_Pr.3.098490[2.227]D(Newbuilding_Pr.(-1)-1.806370[-1.033]D(Scord_Nout_Pr.5.9572[2.781]D(Newbuilding_Pr.(-1)-1.806370[-1.033]D(Scord_Nout_Pr.5.9572[2.781]D(Newbuilding_Pr.(-1)-2.81728[2.781]D(Scord_Nout_Pr.[3.984][2.781]D(Newbuilding_Pr.(-1)-2.816[-1.633]D(Scord_Nout_Pr.[3.981][3.781]D(Newbuilding_Pr.(-1)2.8164[-1.633]D(Scord_Nout_Pr.[3.981][3.781]D	Sample (adjusted): 19	70M08 2011M	02—Included ob	servations: 487 after adju	istments	
D(Fleet_Dwt(-3))2.8582[.663]Percentage_Gdp1.0135[1.082]R'.5839Akaike infriton criterion.8.7S.E. equation20.185Sch=varreision criterion.9.3Log likelihood-2087.5	Variables	Coeff.	t-Statistic	Variables	Coeff.	t-Statistic
R <sup>1</sup> 5.8.39Akaike information criterion8.72101S.E. equation20.185Schwarz riterion9.030618Log likelhood-2087.5Verter autoregressive motor set of the output set output s	D(Fleet_Dwt(-3))	2.8582	[.663]	Percentage_Gdp	1.0135	[1.082]
S.E. equation20.185Schwarz criterion9.030 IILog likelihood~2087.5Vector autoregression colspan="4">Vector autoregression colspan="4"0.0000202798[-5.287]D(Timecharter Rate)1.010410[-1.073]0.00000202798[-6.93]D(Scarop Value)-4.11530[-7.98]0.0000001.23800[-2.277]Percentoge_Geodore5.45972[-7.98]0.0000000201994[-2.271]Vectoregression colspan="4">Vector autoregression colspan="4"0.000000002877.725Vectoregression colspan="4">Vector autoregression colspan="4"0.00000000000000000000 <t< td=""><td><b>R</b><sup>2</sup></td><td>.5839</td><td>Akaike info</td><td>rmation criterion</td><td>8.72</td><td>1014</td></t<>	<b>R</b> <sup>2</sup>	.5839	Akaike info	rmation criterion	8.72	1014
Log likelihood−2087.9Vector autoregression colspan="4">Vector autoregression colspan="4"O(SPOT(-1))-0.8357[-6.613]D(Newbuilding_Pr.(-5))-0.10416[567]D(SPOT(-4))-0.41316[-1.053]D(Fleet_DW(1)1.1109[511]D(SPOT(-5))-1.38809[-5.287]D(Timecharter Rate)15.05347[11.93]D(Newbuilding_Pr.(-1))1.80370[-1.033]D(Secondhand_Pr.)3.098490[2.227]D(Newbuilding_Pr.(-3))-2.471770[-1.397]Percentagesabore.545972[2.78]R*.37509Akalke inter colspan="2.59000".545972[2.78] <t< td=""><td>S.E. equation</td><td>20.185</td><td>Schw</td><td>arz criterion</td><td>9.03</td><td>0618</td></t<>	S.E. equation	20.185	Schw	arz criterion	9.03	0618
Vector autoregression estimates of D(SPUT) PANAMAX (Tankers)           Sample (adjusted): 1970008 2011M02—Included observations: 487 after adjustments           Variables         Coeff.         t-Statistic         Variables         Coeff.         t-Statistic           D(SPOT(-1))        050619         [-1.278]         D(Newbuilding_Pr.(-4))         .706997         [.398]           D(SPOT(-2))        250836         [-6.613]         D(Newbuilding_Pr.(-6))        082006         [567]           D(SPOT(-3))        041316         [-1.059]         C        214986         [-1.51]           D(SPOT(-6))        138809         [-3.633]         D(Ree_Dwt)         -11.11909         [-1.075]           D(SPOT(-6))        302798         [-5.27]         D(Timecharter_Rate)         13.05347         [11.93]           D(Newbuilding_Pr.(-1))         -1.806370         [-1.033]         D(Secondhand_Pr.)         3.098490         [2.227]           D(Newbuilding_Pr.(-2))         1.238302         [.693]         D(Scrap_Value)         -4.115325         [798]           D(Newbuilding_Pr.(-3))         -2.471770         [-1.377]         Percentage_Seaborne         5.45972         [.278]           R*         .375099         Akaike informatiner information riterion         11.950 </td <td>Log likelihood</td> <td>-2087.5</td> <td></td> <td></td> <td></td> <td></td>	Log likelihood	-2087.5				
Sample (adjusted): 1970/008 2011M02—Included observations: 487 after adjustments           Variables         Coeff.         t-Statistic         Variables         Coeff.         t-Statistic           D(SPOT(-1))        050619         [-1.278]         D(Newbuilding_Pr.(-4))         .706997         [.398]           D(SPOT(-2))        250836         [-6.613]         D(Newbuilding_Pr.(-5))         -1.010416         [567]           D(SPOT(-3))        083357         [-2.151]         D(Newbuilding_Pr.(-5))         -1.08206         [051]           D(SPOT(-4))        041316         [-1.059]         C        214986         [151]           D(SPOT(-5))        138809         [-3.683]         D(Fleet_Dwt)         -11.11909         [-1.075]           D(SPOT(-6))        202798         [-5.287]         D(Timecharte_Rate)         15.05347         [11.33]           D(Newbuilding_Pr.(-1))         1.238302         [.693]         D(Scrop_Value)         -4.115325         [-7.798]           D(Newbuilding_Pr.(-3))         -2.471770         [-1.397]         Percentage_Seaborne         .545972         [.278]           R <sup>2</sup> .375099         Akaike information criterion         11.9€602         SE. equation         12.9±562          Log likelihood         -2877	Vector autoregression	n estimates of [	O(SPOT) PANAMA	X (Tankers)		
Variables         Coeff.         t-Statistic         Variables         Coeff.         t-Statistic           D(SPOT(-1))        050619         [-1.278]         D(Newbuilding_Pr.(-4))         .706997         [.398]           D(SPOT(-2))        250836         [-6.613]         D(Newbuilding_Pr.(-5))         -1.010416         [567]           D(SPOT(-3))        083357         [-2.151]         D(Newbuilding_Pr.(-5))         -1.088206         [051]           D(SPOT(-4))        041316         [-1.059]         C        214986         [151]           D(SPOT(-5))        138809         [-3.683]         D(Fleet_Dwt)         -11.11909         [-1.075]           D(SPOT(-6))        202798         [-5.287]         D(Timecharter_Rate)         15.05347         [1.93]           D(Newbuilding_Pr.(-1))         1.238302         [.693]         D(Scrap_Value)         -4.115325         [-7.98]           D(Newbuilding_Pr.(-3))         -2.471770         [-1.397]         Percentage_Seoborne         15.05472         [278]           R <sup>2</sup> .375099         Akaike information criterion         11.26602         SE.equation         12.27562           Log likelihood         -2877.725          Vector autoregression estimates of D(SPOT) HANDYSIZE (Tankers)	Sample (adjusted): 19	70M08 2011M	02—Included obs	servations: 487 after adju	istments	
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Variables	Coeff.	t-Statistic	Variables	Coeff.	t-Statistic
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	D(SPOT(-1))	050619	[-1.278]	D(Newbuilding_Pr.(-4))	.706997	[.398]
D(SPOT(-3))        083357         [-2.151]         D(Newbuilding_Pr.(-6))        08206         [051]           D(SPOT(-4))        041316         [-1.059]         C        214986         [151]           D(SPOT(-5))        138809         [-3.683]         D(Fleet_Dwt)         -11.11909         [-1.075]           D(SPOT(-6))        202798         [-5.287]         D(Timecharter_Rate)         15.05347         [11.93]           D(Newbuilding_Pr.(-1))         -1.806370         [-1.033]         D(Secondhand_Pr.)         3.098490         [2.227]           D(Newbuilding_Pr.(-2))         1.238302         [.693]         D(Scrap_Value)         -4.115325         [798]           D(Newbuilding_Pr.(-3))         -2.471770         [-1.397]         Percentage_Seaborne         5.45972         [.278]           R <sup>2</sup> .375099         Akaike information criterion         11.96602	D(SPOT(-2))	250836	[-6.613]	D(Newbuilding_Pr.(-5))	-1.010416	[567]
$\begin{tabular}{ c c c c c c c c c c c c c c c c c c c$	D(SPOT(-3))	083357	[-2.151]	D(Newbuilding_Pr.(-6))	088206	[051]
D(SPOT(-5))        138809         [-3.683]         D(Fleet_Dwt)         -11.11909         [-1.075]           D(SPOT(-6))        202798         [-5.287]         D(Timecharter_Rate)         15.05347         [11.93]           D(Newbuilding_Pr.(-1))         -1.806370         [-1.033]         D(Scondhand_Pr.)         3.098490         [2.227]           D(Newbuilding_Pr.(-2))         1.238302         [.693]         D(Scrap_Value)         -4.115325         [798]           D(Newbuilding_Pr.(-3))         -2.471770         [-1.397]         Percentage_Seaborne         5.45972         [.278]           R <sup>2</sup> .375099         Akaike information criterion         11	D(SPOT(-4))	041316	[-1.059]	С	214986	[151]
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	D(SPOT(-5))	138809	[-3.683]	D(Fleet_Dwt)	-11.11909	[-1.075]
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	D(SPOT(-6))	202798	[-5.287]	D(Timecharter_Rate)	15.05347	[11.93]
D(Newbuilding_Pr.(-2))1.238302[.693]D(Scrap_Value)-4.115325[.7.98]D(Newbuilding_Pr.(-3))-2.471770[-1.397]Percentage_Seaborne.545972[.278] $R^2$ .375099Akaike intrivinon riterion11.9.S.E. equation29.16946 $S \subset V$ $12.V \subset V$ Log likelihood-2877.725 $V$ $V$ $V$ Vector autoregression = V = V = V = V = V = V = V = V = V =	D(Newbuilding_Pr.(-1))	-1.806370	[-1.033]	D(Secondhand_Pr.)	3.098490	[2.227]
D(Newbuilding_Pr.(-3))         -2.471770         [-1.397]         Percentage_Seaborne         .545972         [.278]           R²         .375099         Akaike information criterion         11.9602           S.E. equation         29.16946         Schwart criterion         12.275           Vector autoregression = 2877.725           Vector autoregression = 50 (SPOT) HANDYSIZE (Tankers)           Sample (adjusted): 1970/6 2011M02—Included obs=vectors: 489 after adjustments           Variables         Coeff.         t-Statistic         Variables         Coeff.         t-Statistic           D(SPOT(-1))        0516         [-1.254]         D(Scrap_Value(-3))        5800         [-0.57]           D(SPOT(-2))        2518         [-6.121]         D(Scrap_Value(-4))         11.105         [1.099]           D(SPOT(-4))        0654         [-1.578]         D(Fleet_Dwt(-1))         14.650         [1.293]           D(SPOT(-4))        0087         [-2.08]         D(Fleet_Dwt(-2))         -1.3105         [-1.183]           D(Newbuilding_Pr.(-1))         2.8106         [1.025]         D(Fleet_Dwt(-4))         -5.6595         [496]           D(Newbuilding_Pr.(-3))         -3.4757         [-1.262]         C        2310         [120] <td>D(Newbuilding_Pr.(-2))</td> <td>1.238302</td> <td>[.693]</td> <td>D(Scrap_Value)</td> <td>-4.115325</td> <td>[798]</td>	D(Newbuilding_Pr.(-2))	1.238302	[.693]	D(Scrap_Value)	-4.115325	[798]
$R^2$ .375099Akaike information criterion11.96602S.E. equation29.16946Schwarz criterion12.27562Log likelihood-2877.725 $-2877.725$ Vector autoregression ====================================	D(Newbuilding_Pr.(-3))	-2.471770	[-1.397]	Percentage_Seaborne	.545972	[.278]
S.E. equation         29.16946         Schwarz criterion         12.27562           Log likelihood         -2877.725             Vector autoregression $= 2877.725$ Sample (adjusted): 1970005 2011M02—Included observations: 489 after adjustents)           Variables         Coeff.         t-Statistic         Variables         Coeff.         t-Statistic           D(SPOT(-1))        0516         [-1.254]         D(Scrap_Value(-3))        5800         [057]           D(SPOT(-2))        2518         [-6.121]         D(Scrap_Value(-4))         11.105         [1.099]           D(SPOT(-2))        0654         [-1.578]         D(Fleet_Dwt(-1))         14.650         [1.293]           D(SPOT(-4))        0087         [208]         D(Fleet_Dwt(-2))         -13.105         [-1.183]           D(Newbuilding_Pr.(-1))         2.8106         [1.025]         D(Fleet_Dwt(-3))        5467         [048]           D(Newbuilding_Pr.(-2))         2.4843         [.897]         D(Fleet_Dwt(-3))        5457         [120]           D(Newbuilding_Pr.(-3))         -3.4757         [-1.262]         C        2310         [120]           D(Newbuilding_Pr.(-4))         25.806         [2.635]         PercentageSeaborne	<b>R</b> <sup>2</sup>	.375099	Akaike i	nformation criterion	11.9	96602
Log likelihood         -2877.725           Vector autoregression estimates of D(SPOT) HANDYSIZE (Tankers)           Sample (adjusted): 1970006 2011M02—Included observations: 489 after adjustents           Variables         Coeff.         t-Statistic         Variables         Coeff.         t-Statistic           D(SPOT(-1))        0516         [-1.254]         D(Scrap_Value(-3))        5800         [057]           D(SPOT(-2))        2518         [-6.121]         D(Scrap_Value(-4))         11.105         [1.099]           D(SPOT(-3))        0654         [-1.578]         D(Fleet_Dwt(-1))         14.650         [1.293]           D(SPOT(-4))        0087         [208]         D(Fleet_Dwt(-2))         -13.105         [-1.183]           D(Newbuilding_Pr.(-1))         2.8106         [1.025]         D(Fleet_Dwt(-3))        5467         [048]           D(Newbuilding_Pr.(-2))         2.4843         [.897]         D(Fleet_Dwt(-4))         -5.6595         [496]           D(Newbuilding_Pr.(-2))         -3.4757         [-1.262]         C        2310         [120]           D(Newbuilding_Pr.(-3))         -3.4757         [-1.248]         D(Timecharter)         5.5870         [10.77]           D(Scrap_Value(-1))         25.806         [2.635] <td>S.E. equation</td> <td>29.16946</td> <td>Sc</td> <td>hwarz criterion</td> <td>12.2</td> <td>27562</td>	S.E. equation	29.16946	Sc	hwarz criterion	12.2	27562
Vector autoregression estimates of D(SPOT) HANDYSIZE (Tankers)Sample (adjusted): 1970M06 2011M02—Included observations: 489 after adjustmentsVariablesCoeff.t-StatisticVariablesCoeff.t-StatisticD(SPOT(-1)) $0516$ $[-1.254]$ D(Scrap_Value(-3)) $5800$ $[057]$ D(SPOT(-2)) $2518$ $[-6.121]$ D(Scrap_Value(-4))11.105[1.099]D(SPOT(-3)) $0654$ $[-1.578]$ D(Fleet_Dwt(-1))14.650[1.293]D(SPOT(-4)) $0087$ $[208]$ D(Fleet_Dwt(-2)) $-13.105$ $[-1.183]$ D(Newbuilding_Pr.(-1))2.8106[1.025]D(Fleet_Dwt(-3)) $5467$ $[048]$ D(Newbuilding_Pr.(-2)) $2.4843$ $[.897]$ D(Fleet_Dwt(-4)) $-5.6595$ $[496]$ D(Newbuilding_Pr.(-3)) $-3.4757$ $[-1.262]$ C $2310$ $[120]$ D(Newbuilding_Pr.(-4)) $-3.3492$ $[-1.248]$ D(Timecharter) $5.5870$ $[10.77]$ D(Scrap_Value(-1))25.806 $[2.635]$ PercentageSeaborne $2.1800$ $[.843]$ D(Scrap_Value(-2)) $2.1378$ $[.213]$ D(Secondhand_Pr.) $-1.2349$ $[706]$ $R^2$ $.2762$ Akaike information criterion $10.85258$ S.E. equation $38.854$ Schwarz criterion $11.53844$ Log likelihood $-2573.4$ $-2573.4$ $-2573.4$ $-2573.4$ $-2573.4$ $-2573.4$ $-2573.4$	Log likelihood	-2877.725				
Sample (adjusted): 1970M06 2011M02—Included observations: 489 after adjustmentsVariablesCoeff.t-StatisticVariablesCoeff.t-Statistic $D(SPOT(-1))$ $0516$ $[-1.254]$ $D(Scrap_Value(-3))$ $5800$ $[057]$ $D(SPOT(-2))$ $2518$ $[-6.121]$ $D(Scrap_Value(-4))$ $11.105$ $[1.099]$ $D(SPOT(-3))$ $0654$ $[-1.578]$ $D(Fleet_Dwt(-1))$ $14.650$ $[1.293]$ $D(SPOT(-4))$ $0087$ $[208]$ $D(Fleet_Dwt(-2))$ $-13.105$ $[-1.183]$ $D(Newbuilding_Pr.(-1))$ $2.8106$ $[1.025]$ $D(Fleet_Dwt(-3))$ $5467$ $[048]$ $D(Newbuilding_Pr.(-2))$ $2.4843$ $[.897]$ $D(Fleet_Dwt(-4))$ $-5.6595$ $[496]$ $D(Newbuilding_Pr.(-3))$ $-3.4757$ $[-1.262]$ $C$ $2310$ $[120]$ $D(Newbuilding_Pr.(-4))$ $-3.3492$ $[-1.248]$ $D(Timecharter)$ $5.5870$ $[10.77]$ $D(Scrap_Value(-1))$ $25.806$ $[2.635]$ PercentageSeaborne $2.1800$ $[.843]$ $D(Scrap_Value(-2))$ $2.1378$ $[.213]$ $D(Secondhand_Pr.)$ $-1.2349$ $[706]$ $R^2$ $.2762$ Akaike information criterion $10.85258$ $S.E.$ equation $38.854$ $Schwarz$ criterion $11.53844$ Log likelihood $-2573.4$ $-2573.4$ $-2573.4$ $-2573.4$ $-2573.4$ $-2573.4$	Vector autoregression	n estimates of [	O(SPOT) HANDYSI	ZE (Tankers)		
VariablesCoeff.t-StatisticVariablesCoeff.t-StatisticD(SPOT(-1))0516[-1.254]D(Scrap_Value(-3))5800[057]D(SPOT(-2))2518[-6.121]D(Scrap_Value(-4))11.105[1.099]D(SPOT(-3))0654[-1.578]D(Fleet_Dwt(-1))14.650[1.293]D(SPOT(-4))0087[208]D(Fleet_Dwt(-2))-13.105[1183]D(Newbuilding_Pr.(-1))2.8106[1.025]D(Fleet_Dwt(-3))5467[048]D(Newbuilding_Pr.(-2))2.4843[.897]D(Fleet_Dwt(-4))-5.6595[496]D(Newbuilding_Pr.(-3))-3.4757[-1.262]C2310[120]D(Newbuilding_Pr.(-4))-3.3492[-1.248]D(Timecharter)5.5870[10.77]D(Scrap_Value(-1))25.806[2.635]PercentageSeaborne2.1800[.843]D(Scrap_Value(-2))2.1378[.213]D(Secondhand_Pr.)-1.2349[706]R².2762Akaike information criterion10.85258S.E. equation38.854Schwarz criterion11.53844Log likelihood-2573.4	Sample (adjusted): 19	70M06 2011M	02—Included obs	servations: 489 after adju	istments	
D(SPOT(-1)) $0516$ $[-1.254]$ D(Scrap_Value(-3)) $5800$ $[057]$ D(SPOT(-2)) $2518$ $[-6.121]$ D(Scrap_Value(-4))11.105 $[1.099]$ D(SPOT(-3)) $0654$ $[-1.578]$ D(Fleet_Dwt(-1))14.650 $[1.293]$ D(SPOT(-4)) $0087$ $[208]$ D(Fleet_Dwt(-2)) $-13.105$ $[-1.183]$ D(Newbuilding_Pr.(-1))2.8106 $[1.025]$ D(Fleet_Dwt(-3)) $5467$ $[048]$ D(Newbuilding_Pr.(-2))2.4843 $[.897]$ D(Fleet_Dwt(-4)) $-5.6595$ $[496]$ D(Newbuilding_Pr.(-3)) $-3.4757$ $[-1.262]$ C $2310$ $[120]$ D(Newbuilding_Pr.(-4)) $-3.3492$ $[-1.248]$ D(Timecharter) $5.5870$ $[10.77]$ D(Scrap_Value(-1))25.806 $[2.635]$ PercentageSeaborne $2.1800$ $[.843]$ D(Scrap_Value(-2)) $2.1378$ $[.213]$ D(Secondhand_Pr.) $-1.2349$ $[706]$ $R^2$ $.2762$ Akaike information criterion $10.85258$ $S.E.$ equation $38.854$ $Schwarz$ criterion $11.53844$ Log likelihood $-2573.4$ $-2573.4$ $-2573.4$ $-2573.4$ $-2573.4$ $-2573.4$ $-2573.4$	Variables	Coeff.	t-Statistic	Variables	Coeff.	t-Statistic
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	D(SPOT(-1))	0516	[-1.254]	D(Scrap_Value(-3))	5800	[057]
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	D(SPOT(-2))	2518	[-6.121]	D(Scrap_Value(-4))	11.105	[1.099]
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	D(SPOT(-3))	0654	[-1.578]	D(Fleet_Dwt(-1))	14.650	[1.293]
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	D(SPOT(-4))	0087	[208]	D(Fleet_Dwt(-2))	-13.105	[-1.183]
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	D(Newbuilding_Pr.(-1))	2.8106	[1.025]	D(Fleet_Dwt(-3))	5467	[048]
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	D(Newbuilding_Pr.(-2))	2.4843	[.897]	D(Fleet_Dwt(-4))	-5.6595	[496]
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	D(Newbuilding_Pr.(-3))	-3.4757	[-1.262]	С	2310	[120]
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	D(Newbuilding_Pr.(-4))	-3.3492	[-1.248]	D(Timecharter)	5.5870	[10.77]
D(Scrap_Value(-2))         2.1378         [.213]         D(Secondhand_Pr.)         -1.2349         [706]           R <sup>2</sup> .2762         Akaike information criterion         10.85258           S.E. equation         38.854         Schwarz criterion         11.53844           Log likelihood         -2573.4	D(Scrap_Value(-1))	25.806	[2.635]	PercentageSeaborne	2.1800	[.843]
R <sup>2</sup> .2762         Akaike information criterion         10.85258           S.E. equation         38.854         Schwarz criterion         11.53844           Log likelihood         -2573.4	D(Scrap_Value(-2))	2.1378	[.213]	D(Secondhand_Pr.)	-1.2349	[706]
S.E. equation38.854Schwarz criterion11.53844Log likelihood-2573.4	<b>R</b> <sup>2</sup>	.2762	Akaike i	nformation criterion	10.8	85258
Log likelihood –2573.4	S.E. equation	38.854	Sc	hwarz criterion	11.	53844
	Log likelihood	-2573.4				

Vector autoregression estimates of D(Spot\_Bulk) CAPESIZE (Bulk carriers)

Sample (adjusted): 1970M08 2011M02—Included observations: 487 after adjustments

Variables	Coeff.	t-Statistic	Variables	Coeff.	t-Statistic
D(Spot_Bulk(-1))	0591	[-1.851]	D(Newbuilding_Pr.(-4))	0856	[-1.295]
D(Spot_Bulk(-2))	1363	[-4.794]	D(Newbuilding_Pr.(-5))	0676	[-1.014]

Table A7. (Continuea)					
Vector autoregression e	stimates of D	(Spot_Bulk) CAPE	SIZE (Bulk carriers)		
Sample (adjusted): 1970	M08 2011M0	2—Included obs	ervations: 487 after adjust	ments	
Variables	Coeff.	t-Statistic	Variables	Coeff.	t-Statistic
D(Spot_Bulk(-3))	0328	[-1.158]	D(Newbuilding_Pr.(-6))	.1603	[2.480]
D(Spot_Bulk(-4))	2717	[-9.486]	С	.0776	[.803]
D(Spot_Bulk(-5))	.1583	[5.462]	D(Fleet_Dwt)	0727	[650]
D(Spot_Bulk(-6))	0253	[926]	D(Timecharter_Rate)	.7755	[19.83]
D(Newbuilding_Pr.(-1))	.0099	[.148]	Percentage_Seaborne	1163	[-1.012]
D(Newbuilding_Pr.(-2))	0206	[302]	D(Scrap_Value)	.1098	[.480]
D(Newbuilding_Pr.(-3))	0454	[682]	D(Secondhand_Pr.)	.4164	[10.02]
<b>R</b> <sup>2</sup>	.7498	Akaike ir	nformation criterion	7.1	73799
S.E. equation	1.7253	Sch	nwarz criterion	7.4	83404
Log likelihood	-1710.8				
Vector autorearession e	stimates of D	(Spot Bulk) PANA	MAX (Bulk carriers)		
Sample (adjusted): 1970	M08 2011M0	2—Included obs	ervations: 487 after adjust	ments	
Variables	Coeff.	t-Statistic	Variables	Coeff.	t-Statistic
D(Spot Bulk(-1))	0553	[-1.217]	D(Secondhand Pr.(-6))	.2392	[2.089]
D(Spot Bulk(-2))	0426	[866]	D(Fleet Dwt(-1))	1697	[213]
D(Spot Bulk(-3))	1719	[-3.513]	D(Fleet Dwt(-2))	3166	[397]
D(Spot Bulk(-4))	.1427	[2.877]	D(Fleet Dwt(-3))	.0710	[.084]
D(Spot Bulk(-5))	0458	[890]	D(Fleet Dwt(-4))	-1.4265	[-1.694]
D(Spot_Bulk(-6))	.0278	[.539]	D(Fleet_Dwt(-5))	.0154	[.018]
D(Newbuilding_Pr.(-1))	.5330	[2.047]	D(Fleet_Dwt(-6))	.6425	[.794]
D(Newbuilding_Pr.(-2))	0184	[069]	D(Scrap_Value(-1))	2.6716	[3.167]
D(Newbuilding_Pr.(-3))	3299	[-1.232]	D(Scrap_Value(-2))	1743	[203]
D(Newbuilding_Pr.(-4))	6005	[-2.350]	D(Scrap_Value(-3))	.6515	[.765]
D(Newbuilding_Pr.(-5))	1179	[473]	D(Scrap_Value(-4))	.0929	[.109]
D(Newbuilding_Pr.(-6))	1061	[440]	D(Scrap_Value(-5))	8632	[-1.029]
D(Secondhand_Pr.(-1))	.0480	[.393]	D(Scrap_Value(-6))	-1.2110	[-1.511]
D(Secondhand_Pr.(-2))	.2172	[1.746]	С	.3625	[1.399]
D(Secondhand_Pr.(-3))	.0688	[.547]	PercentageSeaborne	0839	[343]
D(Secondhand_Pr.(-4))	3391	[-2.646]	D(Timecharter)	1.1785	[15.64]
D(Secondhand_Pr.(-5))	.1745	[1.374]			
<b>R</b> <sup>2</sup>	.4941	Akaike in	formation criterion	10.	46120
S.E. equation	3.5973	Sch	warz criterion	11.	88023
Log likelihood	-2382.3				

Vector autoregression estimates of D(Spot\_Bulk) HANDYMAX (Bulk carriers)

\_

Sample (adjusted): 1970M08 2011M02—Included observations: 487 after adjustments

Variables	Coeff.	t-Statistic	Variables	Coeff.	t-Statistic
D(Spot_Bulk(-1))	.0222	[.547]	D(Secondhand_Pr.(-1))	.0948	[.873]
D(Spot_Bulk(-2))	1853	[-4.447]	D(Secondhand_Pr.(-2))	.3268	[3.047]
D(Spot_Bulk(-3))	0583	[-1.373]	D(Secondhand_Pr.(-3))	.3851	[3.625]
D(Spot_Bulk(-4))	1600	[-3.891]	D(Secondhand_Pr.(-4))	1831	[-1.726]

Idble A7. (Continued)							
Vector autoregression estimates of D(Spot_Bulk) HANDYMAX (Bulk carriers)							
Sample (adjusted): 1970M08 2011M02—Included observations: 487 after adjustments							
Variables	Coeff.	t-Statistic	Variables	Coeff.	t-Statistic		
D(Spot_Bulk(-5))	.0776	[1.874]	D(Secondhand_Pr.(-5))	.0612	[.572]		
D(Spot_Bulk(-6))	0900	[-2.176]	D(Secondhand_Pr.(-6))	.0799	[.790]		
D(Newbuilding_Pr.(-1))	.1567	[.662]	С	.1889	[1.291]		
D(Newbuilding_Pr.(-2))	2538	[-1.061]	Percentage_Seaborne	0477	[279]		
D(Newbuilding_Pr.(-3))	4324	[-1.823]	D(Timecharter_Rate)	1.7836	[18.26]		
D(Newbuilding_Pr.(-4))	.3287	[1.394]	D(Scrap_Value)	0944	[136]		
D(Newbuilding_Pr.(-5))	1095	[469]	D(Fleet_Dwt)	55133	[-1.405]		
D(Newbuilding_Pr.(-6))	2725	[-1.233]					
<b>R</b> <sup>2</sup>	.6335	Akaike information criterion		9.032675			
S.E. equation	2.5583	Schwarz criterion		9.626084			
Log likelihood	-2130.4						

# Table A8. VECM estimations (Tankers—Bulk carriers)

Vector error correction estimates (U-VLCC-Tankers)

Sample (adjusted): 1970M08 2011M02—Included observations: 487 after adjustments, t-statistics in []

Cointegrating Eq:	Coint. Eq1				
SPOT(-1)	1.000000				
Secondhand_Pr.(-1)	1.540622	[1.34216]			
Newbuilding_Pr.(-1)	-5.644820	[-3.87671]			
Scrap_Value(-1)	27.95869	[3.57976]			
Fleet_Dwt(-1)	573406	[-1.39674]			
С	180.4849				
Error Correction:	D(SPOT)	D(Secondhand_Prices)	D(Newbuilding_Prices)	D(Scrap Value)	D(Fleet_Dwt)
Coint. Eq1	003354	.002087	.004285	000558	.001798
	[46361]	[1.12219]	[3.43981]	[-1.20114]	[3.64057]
<i>R</i> <sup>2</sup>	.801158	.262991	.312918	.218149	.636380
S.E. equation	10.41086	2.675403	1.792557	.668337	.710465
Log likelihood	Akaike i	nformation criterion	Schwarz criterion		
-4825.421		20.53561	22.04063		

# Vector error correction estimates (Suezmax-Tankers)

Sample (adjusted): 1970M06 2011M02—Included observations: 489 after adjustments, t-statistics in []

Cointegrating Eq:	Coint. Eq1				
SPOT(-1)	1.000000				
Secondhand_Pr.(-1)	-2.978870	[-2.29751]			
Newbuilding_Pr.(-1)	808660	[54569]			
Scrap_Value(-1)	30.88417	[3.69128]			
Fleet_Dwt(-1)	-1.515290	[-1.05679]			
С	-32.46050				
Error Correction:	D(SPOT)	D(Secondhand_Prices)	D(Newbuilding_Prices)	D(Scrap Value)	D(Fleet_Dwt)

# Table A8. (Continued)

## Vector error correction estimates (Suezmax-Tankers)

#### Sample (adjusted): 1970M06 2011M02—Included observations: 489 after adjustments, t-statistics in []

Cointegrating Eq:	Coint. Eq1				
Coint. Eq1	048016	000395	.001950	001276	.000418
	[-3.34101]	[25855]	[1.89795]	[-2.85593]	[1.91475]
<b>R</b> <sup>2</sup>	.601082	.172282	.286858	.114320	.277123
S.E. equation	16.25639	1.728756	1.162324	.505564	.246819
Log likelihood	Akaike information criterion		Schw	varz criterion	
-4014.327	16.92976		18.00143		

#### Vector error correction estimates (Aframax-Tankers)

Sample (adjusted): 1970M08 2011M02—Included observations: 487 after adjustments, t-statistics in []

Cointegrating Eq:	Coint. Eq1	Coint. Eq2	
SPOT(-1)	1.000000	.000000	
Fleet_Dwt(-1)	.000000	1.000000	
Secondhand_Prices(-1)	-3.055570	11.93197	
	[-4.02398]	[3.37157]	
С	-26.33813	-373.9440	
Error correction	D(SPOT)	D(Fleet_Dwt)	D(Secondhand_Prices)
Coint. Eq1	092061	.000636	.003754
	[-3.55778]	[2.26001]	[2.27193]
Coint. Eq2	010109	.000272	2.37E-05
	[-1.73067]	[4.28807]	[.06360]
$R^2$	.603388	.370946	.308237
S.E. equation	19.85839	.216011	1.268140
Log likelihood	Akaike information criterion		Schwarz criterion
-2855.992	12.0	12.06157	

#### Vector error correction estimates (Panamax–Tankers)

# Sample (adjusted): 1970M06 2011M02—Included observations: 489 after adjustments, t-statistics in []

		<b>, , ,</b>	
Cointegrating Eq:	Coint. Eq1	Coint. Eq2	
SPOT(-1)	1.000000	.000000	
Newbuilding_Prices(-1)	.000000	1.000000	
Fleet_Dwt(-1)	5.255168	.996341	
	[2.80539]	[1.93233]	
С	-237.7539	-49.42429	
Error correction	D(SPOT)	D(Newbuilding_Prices)	D(Fleet_Dwt)
Coint. Eq1	216999	.001189	.000281
	[-7.98795]	[1.63786]	[2.69427]
Coint. Eq2	.512133	010454	.002103
	[3.49766]	[-2.67226]	[3.73625]
<b>R</b> <sup>2</sup>	.413340	.215813	.313996
S.E. equation	28.73942	.767857	.110461
Log likelihood	Akaike ir	nformation criterion	Schwarz criterion
-2488.050		10.43374	10.97386

# Table A8. (Continued)

#### Vector error correction estimates (Handysize–Tankers)

#### Sample (adjusted): 1970M08 2011M02—Included observations: 487 after adjustments, t-statistics in []

Cointegrating Eq:	Coint. Eq1			
SPOT(-1)	1.000000			
Newbuilding_Prices(-1)	-9.065271			
	[-5.80248]			
Scrap_Value(-1)	53.99123			
	[3.31459]			
С	-34.48705			
Error correction:	D(SPOT)	D(Newbuilding_Prices)	D(Scrap_Value)	
Coint. Eq1	147034	.002438	000357	
	[-4.42416]	[4.34322]	[-2.17613]	
$R^2$	.316044	.230622	.056724	
S.E. equation	37.48530	.633099	.185136	
Log likelihood	Akaike	Akaike information criterion		
-2756.459		11.62817	12.27318	

# Vector error correction estimates (Capesize-Bulk carriers)

Sample (adjusted): 1970M08 2011M02—Included observations: 487 after adjustments, t-statistics in []

Cointegrating Eq:	Coint. Eq1	
Spot_Bulk(-1)	1.000000	
Newbuilding_Prices(-1)	970013	
	[-6.40975]	
С	31.27048	
Error correction	D(Spot_Bulk)	D(Newbuilding_Prices)
Coint. Eq1	025728	.022566
	[-2.45942]	[3.16150]
<b>R</b> <sup>2</sup>	.752692	.305278
S.E. equation	1.717535	1.171876
Log likelihood	Akaike information criterion	Schwarz criterion
-1703.287	7.159291	7.503296

Vector error correction estimates (PanamaxB–Bulk carriers)

Sample (adjusted): 1970M06 2011M02—Included observations: 489 after adjustments, t-statistics in []

Cointegrating Eq:	Coint. Eq1	Coint. Eq2	Coint. Eq3	Coint. Eq4	
Spot_Bulk(-1)	1.000000	.000000	.000000	.000000	
Secondhand_Pr.(-1)	.000000	1.000000	.000000	.000000	
Newbuilding_Pr. (–1)	.000000	.000000	1.000000	.000000	
Fleet_Dwt(-1)	.000000	.000000	.000000	1.000000	
Scrap_Value(-1)	-21.55242	-15.85086	-10.33899	10.98117	
	[-7.76574]	[-9.72067]	[-7.42110]	[1.42054]	
С	25.35444	18.41539	368095	-76.77063	
Error correction:	D(Spot_Bulk)	D(Secondhand_Prices)	D(Newbuilding_Prices)	D(Fleet_Dwt)	D(Scrap_Value)
Coint. Eq1	083451	.010823	.003753	.003252	.005962
	[-2.86145]	[.88385]	[.70622]	[1.91473]	[3.25534]
Coint. Eq2	.059989	079856	.004048	006101	003896

# Table A8. (Continued)

#### Vector error correction estimates (PanamaxB–Bulk carriers)

#### Sample (adjusted): 1970M06 2011M02—Included observations: 489 after adjustments, t-statistics in []

Cointegrating Eq:	Coint. Eq1	Coint. Eq2	Coint. Eq3	Coint. Eq4	
	[1.12293]	[-3.56003]	[.41582]	[-1.96109]	[-1.16120]
Coint. Eq3	.131376	.052994	038739	.003048	004132
	[2.10746]	[2.02456]	[-3.41006]	[.83974]	[-1.05545]
Coint. Eq4	.012148	004285	003120	.001291	.000112
	[1.65662]	[-1.39167]	[-2.33473]	[3.02216]	[.24233]
<b>R</b> <sup>2</sup>	.500445	.660719	.405204	.594102	.408980
S.E. equation	3.544036	1.488113	.645845	.206384	.222560
Log likelihood	Akaike information criterion	Schwarz criterion			
-2404.526	10.46841	11.79728			

# Vector error correction estimates (Handymax–Bulk carriers)

Sample (adjusted): 1970M08 2011M02—Included observations: 487 after adjustments, t-statistics in []

Cointegrating Eq:	Coint. Eq1 Coint. Eq2		Coint. Eq3		
Spot_Bulk(-1)	1.000000	.000000	.000000		
Secondhand_Prices(-1)	.000000	.000000 1.000000			
Newbuilding_Prices(-1)	.000000	.000000. 000000.			
Fleet_Dwt(-1)	3.235324	1.582158	1.384436		
	[2.55074]	[2.24684]	[2.74668]		
С	-148.8089	-78.34988	-77.46503		
Error Correction:	D(Spot_Bulk)	D(Secondhand_Prices)	D(Newbuilding_Prices)	D(Fleet_Dwt)	
Coint. Eq1	020136	.004040	.008559	.003310	
	[-1.22390]	[.65037]	[2.62953]	[3.48403]	
Coint. Eq2	.036944	030550	006100	008376	
	[1.00147]	[-2.19343]	[83573]	[-3.93235]	
Coint. Eq3	.013774	.029477	013489	.003913	
	[.40493]	[2.29525]	[-2.00429]	[1.99238]	
<i>R</i> <sup>2</sup>	.646993	.734067	.438884	.777903	
S.E. equation	2.532805	.956279	.501127 .146245		
Log likelihood	Akaike i	nformation criterion	Schwarz criterion		
-1842.059		8.123444	9.293062		

# Table A9. ARMA estimations

ARMA models								
Sample period				1970:0	1–2011:02			
Estimated	Dependent variable							
parameter	Deseason spot U-VLCC	Deseason spot Suezmax	Deseason spot Aframax	Deseason spot Panamax	Deseason spot Handysize	Deseason spot Capesize	Deseason spot Panamax Bulk	Deseason spot Handymax
С	50.51440 (7.289256)	84.35932 (7.766115)	109.7379 (8.757114)	65.13086 (2.061293)	196.0753 (9.558014)	.004305 (.598348)	2.528280 (.339349)	-3.569690 (381624)
AR(1)	-1.283094 (-37.74231)	.107290 (2.071504)	832105 (-12.48406)	.477334 (3.120405)	.698240 (13.64264)	676455 (-6.633687)	.670766 (8.249042)	.953212 (19.96283)
AR(2)	570836 (-10.07574)	177158 (-3.585934)	186717 (-4.195845)	327766 (-2.437536)	209087 (-3.524179)	856443 (-12.42586)	537376 (-6.298731)	.396836 (6.828252)
AR(3)	.141185 (2.421285)	.772797 (17.12819)	.610561 (13.03950)	.558373 (6.590533)	611883 (-16.21170)	635871 (-5.302165)	.710012 (10.78866)	746559 (-12.41586)
AR(4)	.934746 (17.95769)		.662752 (10.81503)		.916437 (24.10023)	.096732 (1.500675)		.559497 (9.074051)
AR(5)	.821065 (27.48851)				203068 (-3.516742)	147111 (-2.651800)		651510 (-10.73098)
AR(6)					.157016 (3.245630)			280714 (-4.599328)
AR(7)								.969153 (16.12959)
AR(8)								294555 (-6.060243)
SAR(12)	.699167 (20.19190)		.334203 (7.550390)	.716029 (14.43753)	.727717 (14.33190)	774569 (-10.67135)		
MA(1)	2.246656 (82.48329)	.890617 (20.77912)	1.850083 (40.35599)	.590487 (3.761955)	.221006 (11.31165)	1.088000 (12.44610)	.555944 (6.226538)	.389015 (23.83258)
MA(2)	2.602970 (43.01914)	.897622 (22.64891)	1.843245 (42.44613)	.597314 (5.351663)	.198839 (9.345439)	1.104382 (25.47100)	1.072724 (10.79403)	266350 (-17.68404)
MA(3)	2.161397 (38.09550)		.920578 (20.41714)		.960425 (49.97051)	.888543 (10.81919)	.195430 (1.944928)	.252737 (15.56664)
MA(4)	.947539 (39.66572)						.175612 (2.517423)	262681 (-17.69877)
MA(5)							227382 (-3.952912)	.385901 (26.58436)
MA(6)								.966484 (63.16826)
SMA(12)	706648 (-14.83996)	.140662 (2.998067)		660152 (-10.56428)	667197 (-10.27292)	.820005 (11.83217)		
AIC	8.342932	9.081541	9.232544	9.541650	10.06605	-1.364143	5.850106	5.480243
SIC	8.447776	9.141368	9.311051	9.620033	10.17106	-1.267883	5.935573	5.618061
DW	2.001919	2.096460	2.087147	1.975731	2.001162	1.998050	2.038217	2.019004

# Table A10. GARCH estimations

GARCH model	s										
Sample period	1970:01–2011:02										
Estimated		Dependent variable									
parameter	Deseason spot U-VLCC	Deseason spot Suezmax	Deseason spot Aframax	Deseason spot Panamax	Deseason spot Handysize	Deseason spot Capesize	Deseason spot Panamax Bulk	Deseason spot Handymax			
С	5.691304 (2.213809)	6.466746 (2.867686)	17.89197 (2.199346)	108.3865 (3.505629)	139.9965 (3.156653)	.028021 (3.400383)	.106843 (3.561445)	.102673 (3.375823)			
ARCH (1)	.392118 (12.32730)	.455110 (9.027228)	.211607 (8.028785)	.245802 (6.067745)	.241939 (12.68916)	.462388 (7.730518)	.184306 (3.519282)	.340177 (7.806101)			
ARCH (2)	.444280 (10.53461)	262658 (-4.535314)	.210654 (8.342708)	.237916 (6.516534)	.224924 (7.449137)	360060 (-3.151224)	172317 (-2.215324)				
ARCH (3)	.337734 (9.539731)	.296729 (6.757749)	.205676 (7.318297)	.235949 (6.312831)	.182055 (9.840213)	.212833 (3.373868)	.134430 (2.810678)				
ARCH (4)			.225983 (8.842686)	.246055 (6.054769)	.202829 (91.19500)						
GARCH (1)	195273 (-3.900444)	.731743 (25.29878)	082794 (-2.620347)	128263 (-2.849323)	328229 (-9.388411)	1.563985 (23.15183)	2.024000 (135.6112)	.992152 (7.109913)			
GARCH (2)	127651 (-3.358435)	629088 (-19.46479)	248008 (-7.881385)	180311 (-5.838934)	141188 (-4.193502)	-1.321975 (-21.73843)	-1.881301 (-470.8925)	581392 (-3.200924)			
GARCH (3)	.493274 (10.55966)	.493006 (22.84013)	197958 (-7.981229)	335436 (-11.11069)	096629 (-4.260191)	.506914 (20.39618)	.717883 (41.94791)	.297335 (3.182537)			
GARCH (4)			.811815 (30.57328)	.696045 (19.24948)	.731271 (31.20748)						
AIC	7.810066	8.277758	8.835272	9.417321	9.995540	3.102276	4.625304	4.098563			
SIC	7.895269	8.354441	8.928995	9.511044	10.09778	3.187479	4.710507	4.158205			
DW	1.967438	2.024944	1.936013	1.782192	1.913008	1.270328	1.561924	1.268188			

# Table A11. E-GARCH estimations

E-GARCH models										
Sample period	1970:01–2011:02									
Estimated parameter	Dependent variable									
	Deseason spot U-VLCC	Deseason spot Suezmax	Deseason spot Aframax	Deseason spot Panamax	Deseason spot Handysize	Deseason spot Capesize	Deseason spot Panamax Bulk	Deseason spot Handymax		
С	.080997 (1.154514)	.189936 (2.655860)	.174026 (2.254872)	.122143 (1.537955)	.210860 (2.895870)	112579 (-2.516638)	113772 (-3.472137)	144885 (-3.930217)		
ARCH (1)	.173842 (2.711991)		.079576 (1.292355)	.131530 (2.105265)	055893 (-2.990198)	.132892 (2.607516)	.211706 (4.574413)	.209561 (4.354164)		
GARCH (1)	.949529 (85.63437)	.950800 (70.29388)	.952892 (84.38945)	.963147 (80.57513)	1.153938 (439.2297)	.468422 (5.440948)	1.030720 (18.77174)	.697731 (9.252560)		
GARCH (2)					517418 (-26.98499)	.393596 (5.374048)	167527 (-2.810100)	.851964 (10.64576)		
GARCH (3)					.779859 (38.02508)	.125720 (1.530027)	.181747 (4.066184)	-1.198651 (-8.040732)		
GARCH (4)					446274 (-128.7171)		328864 (-6.964393)	.661886 (5.539970)		

# Table A11. (Continued)

E-GARCH models										
Sample period	1970:01–2011:02									
Estimated parameter	Dependent variable									
	Deseason spot U-VLCC	Deseason spot Suezmax	Deseason spot Aframax	Deseason spot Panamax	Deseason spot Handysize	Deseason spot Capesize	Deseason spot Panamax Bulk	Deseason spot Handymax		
GARCH (5)							1.044272 (17.07599)	.615147 (6.728311)		
GARCH (6)							787274 (-12.92941)	649414 (-9.106182)		
GED Param- eter	1.236053 (12.21719)	1.117241 (13.65458)	1.106140 (13.48880)	1.218839 (12.26160)	1.177610 (10.27545)	1.333881 (12.36540)	1.396545 (10.06284)	1.342111 (11.22765)		
γ	.365070 (7.176910)	.462934 (9.851868)	.326644 (6.575959)	.338859 (7.615534)	.290796 (9.314992)	.526844 (10.81342)	.140141 (4.630916)	.187258 (5.892187)		
AIC	7.578090	8.061229	8.642392	9.267484	9.798426	2.929507	4.470121	3.922165		
SIC	7.637732	8.120871	8.710554	9.327126	9.892150	3.014710	4.580885	4.032929		
DW	1.985217	1.986143	1.910441	1.814212	1.977502	1.253481	1.538184	1.266462		



#### © 2014 The Author(s). This open access article is distributed under a Creative Commons Attribution (CC-BY) 3.0 license. You are free to:

Share — copy and redistribute the material in any medium or format

Adapt — remix, transform, and build upon the material for any purpose, even commercially.

The licensor cannot revoke these freedoms as long as you follow the license terms.

Under the following terms:

Attribution — You must give appropriate credit, provide a link to the license, and indicate if changes were made. You may do so in any reasonable manner, but not in any way that suggests the licensor endorses you or your use. No additional restrictions

You may not apply legal terms or technological measures that legally restrict others from doing anything the license permits.

# Cogent Economics & Finance (ISSN: 2332-2039) is published by Cogent OA, part of Taylor & Francis Group. Publishing with Cogent OA ensures:

- Immediate, universal access to your article on publication
- High visibility and discoverability via the Cogent OA website as well as Taylor & Francis Online
- Download and citation statistics for your article
- Rapid online publication
- Input from, and dialog with, expert editors and editorial boards
- Retention of full copyright of your article
- Guaranteed legacy preservation of your article
- Discounts and waivers for authors in developing regions

Submit your manuscript to a Cogent OA journal at www.CogentOA.com