RESEARCH ARTICLE

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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, G. Veriti 84, Chios 82100, 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.
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’ dead-weight 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. Cyclicity 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 academicians 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 cyclicity 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
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—$I(0,0)$. 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 $H_0: \phi = 0$ and $\beta = 0$ (stochastic trend) versus $H_1: \phi < 0$ and $\beta \neq 0$ (deterministic trend) and estimates the following regression:

$$\Delta y_t = \phi y_{t-1} + \beta t + \sum_{j=1}^{p-1} \alpha_j \Delta y_{t-j} + \epsilon_t$$  \hspace{1cm} (1)
where \( \varphi = -\alpha(1) \) and \( \alpha^* = -\alpha_j + \cdots + \alpha_p \). 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:

\[
\Delta Y_t = \varphi + \sum_{i=1}^{p} \alpha_i \Delta Y_{t-1} + \epsilon_t \tag{2}
\]

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 \( [H_0: \gamma_t - I(0)] \) against the alternative that it is \( [H_1: \gamma_t - I(1)] \). 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. 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).

| Sample size | F-test | Critical values 5% level (t-statistic) |
|-------------|--------|--------------------------------------|
| 50          | 6.73   | -3.49                                |
| 100         | 6.49   | -3.45                                |
| [500]       | [6.30] | [-3.42]                              |
| \( \infty \) | 6.25   | -3.41                                |

Source: Author (adaptation from Heij, De Boer, Franses, Kloek, and Van Dijk [2004]).
With a VAR, it is necessary to specify only two things, (1) endogenous and exogenous 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:

\[
\Delta Y_t = \varphi + \sum_{i=1}^{p} a_i \Delta Y_{t-i} + \sum_{j=1}^{q} \gamma_j X_{t-j} + \epsilon_t
\]  

(3)

where \(a_i\) 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 (Lütkepohl & Kratzig, 2004).

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

The VECM model is expressed as:

\[
\Delta Y_t = -\Phi(1)(Y_{t-1} - \mu) + \sum_{j=1}^{p-1} \Gamma_j \Delta Y_{t-j} + \epsilon_t
\]  

(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 distinctly 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:

\[
Y_t = \sum_{i=1}^{p} \phi_i Y_{t-i} + \epsilon_t + \sum_{j=1}^{q} \theta_j \epsilon_{t-j}
\]

where \( p \) and \( q \) are the orders of AR and MA terms respectively and \( \phi \) and \( \theta \) 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:

\[
(1 - \alpha_1 L - \alpha_2 L^2 - \cdots - \alpha_i L^i)(1 - \varphi L^{12}) = (1 - \beta_1 L - \beta_2 L^2 - \cdots - \beta_j L^j)(1 - \theta L^{12}) \epsilon_t
\]

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:

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

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

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:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \lambda_1 \sigma_{t-1}^2$$  \hspace{1cm} (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:

$$\log(\sigma_t^2) = a_0 + a_1 \log(\sigma_{t-1}^2) + \gamma \frac{\epsilon_{t-1}}{\sigma_{t-1}} + \beta \frac{|\epsilon_{t-1}|}{\sigma_{t-1}}$$  \hspace{1cm} (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:

$$Y_t = \chi \theta + \delta \sigma_t^2 + \epsilon_t$$  \hspace{1cm} (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 $\epsilon_t$ have been estimated from the mean equation. Then an auxiliary regression of the squared residuals ($\epsilon_t^2$) is estimated upon the lagged squared terms ($\epsilon_{t-1}^2, \ldots, \epsilon_{t-q}^2$) 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). 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:

\[ Y_{c,t+h} = \sum_{i=1}^{n} w_i Y_{i,t+h} \]

where \( Y_{c,t+h} \) is the combined forecast, \( w \) is the weight average, and \( Y_{i,t+h} \) 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):

| Tankers | Bulk carriers |
|---------|---------------|
| 1. ULCC–VLCC (200,000 dwt+) | 1. Capesize (80,000 dwt+) |
| 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) | |
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 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 3. Examinant variables for multiple equations models |
|----------------------------------------------------------|
| **Endogenous**                                           |
| Spot rates ($/day)                                       |
| Timecharter rate ($/day)                                 |
| Second-hand prices 5-year ($ million)                    |
| Newbuilding prices ($ million)                           |
| Scrap prices ($/ldt)                                     |
| Fleet capacity (million dwt)                             |
| **Exogenous**                                           |
| Worldwide GDP                                           |
| Seaborne trade (million tones)                           |

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

| Hypothesized No. of CE(s) | Johansen cointegration test | Trace statistic | .05 Critical value | Prob.** |
|---------------------------|----------------------------|----------------|---------------------|--------|
| **ULCC-VLCC:** Endogenous variables: spot, fleet, secondhand, newbuilding, scrap | | | | |
| None*                     |                           |                 |                    |        |
| At most 1                 | .089433                   | 84.16515        | 69.81889           | .0023  |
| At most 2                 | .041545                   | 38.53912        | 47.85613           | .2790  |
| At most 3                 | .022285                   | 17.87441        | 29.79707           | .5754  |
| At most 4                 | .010409                   | 6.898775        | 15.49471           | .5895  |
| **Suezmax:** Endogenous variables: spot, fleet, secondhand, 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                   | 1.87889         | 3.841466           | .6647  |
| **Aframax:** Endogenous variables: spot, 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: spot, newbuilding, fleet | | | | |
| None*                     | .133653                   | 102.1103        | 29.79707           | .0000  |
| At most 1                 | .060149                   | 31.95356        | 15.49471           | .0011  |
| At most 2                 | .003006                   | 1.619169        | 3.841466           | .2012  |
| **Handysize:** Endogenous variables: spot, newbuilding, scrap | | | | |
| 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, newbuilding | | | | |
| None*                     | .042562                   | 28.31457        | 15.49471           | .0004* |
| At most 1                 | .014540                   | 7.133080        | 3.841466           | .0076  |
| **Panamax Bulk:** Endogenous variables: spot, fleet, secondhand, newbuilding, scrap | | | | |
| 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: spot, fleet, secondhand, newbuilding | | | | |
| None*                     | .072522                   | 78.95723        | 47.85613           | .0000  |
| At most 1                 | .045369                   | 42.29303        | 29.79707           | .011   |
| 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.
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\(^6\)). 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 (.360) 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 6. Long-run equilibrium relations and adjustment coefficients

| Market       | Spot \(_t\) = | Secondhand \(_t\) | Newbuilding \(_t\) | Scrap \(_t\) | Fleet \(_t\) | \(\%\)  |
|--------------|---------------|-------------------|-------------------|-------------|-------------|--------|
| ULCC-VLCC    | \(-1.54\)     | .564              | -.2796            | .58         | -.180.48    | 1.14%  |
| Suezmax      | \(+2.98\)     | .81               | -.30.88           | 1.52        | -.32.46     | 5.21%  |
| Aframax      | \(-.306\)     | .26              | -.217375          | 1.21        | 21.85%      |
| Handysize    | \(-9.22\)     | .38              | -.59.399          | 34.49       | 14.98%      |
| Capesize     | \(-2.57\)     | 2.26             | -.31.27           | 4.83%       |
| Panamax Bulk | 21.55         | 25.35            | -.835%            | 10.14%      |
| Handymax     | \(-3.24\)     | .4              | -.2012%           | 3.60%       |

Note: Long-run multipliers in italics and adjustment coefficients in bold.
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 \[ \gamma = (.365 \text{ U-VLCC}), (.463 \text{ Suezmax}), (.327 \text{ Aframax}), (.339 \text{ Panamax}), \text{ and } (.291 \text{ Handysize}) \].

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 the magnitude of volatility in relation to negative innovations, as in tanker market \[ \gamma = (.527 \text{ Capesize}), (.140 \text{ Panamax Bulk}), \text{ and } (.187 \text{ Handymax}) \]. Analytical estimations of E-GARCH are presented in Appendix-Table A11.

| Table 7. ARMA orders and lag operators for each vessel type |
|-------------------------------------------------------------|
| **ULCC-VLCC: SARMA (5,4)**                                  |
| Spot, = 50.51 + u_t                                          |
| (1 + 1.28L)(1 + 5.7L)(1 − 1.4L)(1 − 9.3L)(1 − 8.2L)(1 − 0.7L)u_t = (1 + 2.25L)(1 + 2.60L)(1 + 2.16L)(1 + 0.95L)(1 − 0.71L)^2 \epsilon_t |
| **Suezmax: SARMA (3,2)**                                     |
| Spot, = 84.36 + u_t                                          |
| (1 − 0.1L)(1 + 0.18L)(1 + 0.77L)u_t = (1 − 0.89L)(1 − 0.90L)(1 − 0.14L)^2 \epsilon_t |
| **Aframax: SARMA (4,3)**                                     |
| Spot, = 109.74 + u_t                                         |
| (1 + 0.83L)(1 + 0.19L)(1 − 0.66L)(1 + 0.33L)(1 − 1.85L)(1 − 1.84L)(1 − 0.92L)^4 \epsilon_t |
| **Panamax: SARMA (3,2)**                                     |
| Spot, = 65.13 + u_t                                         |
| (1 − 0.47L)(1 + 0.33L)(1 − 0.56L)(1 − 0.72L)(1 + 0.59L)(1 − 0.60L)(1 + 0.66L)^3 \epsilon_t |
| **Handysize: SARMA (6,3)**                                   |
| Spot, = 196.08 + u_t                                         |
| (1 + 0.1L)(1 + 0.68L)(1 − 0.61L)(1 + 0.20L)(1 − 0.15L)(1 − 0.73L)(1 − 1.09L)(1 − 1.00L)(1 − 0.89L)(1 − 0.82L)^4 \epsilon_t |
| **Capesize: SARMA (5,3)**                                    |
| Spot, = .004 + u_t                                           |
| (1 + 0.68L)(1 + 0.86L)(1 − 0.64L)(1 − 1.0L)(1 + 0.15L)(1 − 0.77L)(1 + 1.0L)(1 − 1.0)(1 − 0.9L)(1 + 0.9L)^2 \epsilon_t |
| **Panamax Bulk: ARMA (3,5)**                                |
| Spot, = 2.53 + u_t                                            |
| (1 + 0.67L)(1 + 0.53L)(1 − 0.71L)(1 − 0.56L)(1 − 1.07L)(1 − 0.19L)(1 + 0.22L)(1 − 0.22L)(1 − 0.22L)(1 − 0.22L)(1 − 0.22L)^2 \epsilon_t |
| **Handymax: ARMA (8,6)**                                    |
| Spot, = −3.57 + u_t                                           |
| (1 + 1.95L)(1 − 0.60L)(1 + 0.75L)(1 − 0.56L)(1 + 0.65L)(1 + 0.28L)(1 − 0.97L)(1 + 0.29L)(1 − 0.39L)(1 + 0.27L)(1 − 0.25L)(1 + 0.26L)(1 − 0.39L)(1 − 0.97L)^8 \epsilon_t |
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.

### Table 8. GARCH and E-GARCH models in bulk shipping

| 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)             |

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

| Vessels       | Models          | Theil | RMSE   | Theil | RMSE   | Theil | RMSE   | Theil | RMSE   |
|---------------|-----------------|-------|--------|-------|--------|-------|--------|-------|--------|
|               | ARMA GARCH EGARCH VAR VECM |       |        |       |        |       |        |       |        |
| ULCC-VLCC     | .093            | 19.04 | .086   | 8.326 | .087   | 8.467 | .071   | 6.757 | .075   | 7.101  |
| Suezmax       | .091            | 17.11 | .090   | 17.05 | .089   | 16.73 | .090   | 17.32 | .089   | 18.86  |
| Aframax       | .109            | 26.20 | .096   | 23.09 | .097   | 23.15 | .097   | 23.24 | .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            | 4.738 | .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  |

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.

### Table 10. Evaluation of ex-ante forecast 12 months—Theil and RMSE criterions

| Criteria      | Models          | U-VLCC          | Suezmax         | Aframax         | Panamax         |
|---------------|-----------------|-----------------|-----------------|-----------------|-----------------|
|               | VAR Combining   | E-GARCH Combining | VECM Combining | VECM Combining |
| 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          |

| Criteria      | Models          | Handysize      | Capesize       | Panamax Bulk    | Handymax        |
|---------------|-----------------|----------------|----------------|-----------------|-----------------|
|               | ARMA Combining  | VECM Combining | VECM Combining | VECM Combining  |
| 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).
Figure 1. Ex-post and ex-ante forecasts for U-VLCC and Suezmax markets.

Figure 2. Ex-post and ex-ante forecasts for Aframax and Panamax 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.
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Author details
N.D. Geomelos¹
E-mail: n.geomelos@chios.aegean.gr
E. Xideas¹
E-mail: e.xideas@aegean.gr
¹ Department of Shipping, Trade and Transport, University of the Aegean, G. Veriti 84, Chios 82100, Greece.

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. 699–700).
3. As Sims (1980) noticed, the specification of some of the 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.

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Appendix

Figure A1. Correlograms of ULCC-VLCC and Capesize.
### Table A1. Test results of unit root and stationarity tests in tanker and bulk carrier market (ADF, PP, KPSS)

#### Tankers

| Ships variables | Unit root tests (constant) — ADF | Unit root tests (constant and trend) — ADF | Unit root tests (constant) — PP | Unit root tests (constant and trend) — PP | KPSS |
|-----------------|-----------------------------------|--------------------------------------------|---------------------------------|--------------------------------------------|------|
|                 | Constant | Lags  | F-statistic | Constant | Lags  | F-statistic | Intercept | Lags | Intercept | Lags |
| **ULCC-VLCC**   |          |       |             | Constant | Lags  | F-statistic | Intercept | Lags | Intercept | Lags |
| SPOT            | -4.349763 | 14    | 7.15        | -4.485632 | 15    | .63         | -6.517016 | 1    | -6.535936 | 1    |
| LogSPOT         | -5.061852 | 1     | 5.69        | -5.271801 | 1     | 1.13        | -5.143787 | 1    | -5.383386 | 1    |
| Timecharter_Rate| -6.299262 | 14    | 6.79        | -6.372307 | 15    | .33         | -5.550506 | 3    | -5.554937 | 3    |
| LogTimecharter_Rate| -3.400368 | 12    | 5.55        | -3.556815 | 12    | .59         | -3.524808 | 3    | -3.614347 | 3    |

**Suezmax**

| SPOT            | -5.422573 | 2     | 9.98        | -5.977616 | 3     | 3.04        | -5.363671 | 2    | -5.948075 | 2    |
| LogSPOT         | -6.029574 | 1     | 7.81        | -6.271390 | 1     | 3.41        | -3.681763 | 6    | -4.582409 | 5    |
| Timecharter_Rate| -3.195757 | 14    | 4.03        | -3.812497 | 15    | 2.19        | -4.292573 | 3    | -4.922830 | 2    |
| LogTimecharter_Rate| -2.992747 | 7     | 4.10        | -4.038741 | 7     | 3.85        | -2.969223 | 1    | -3.703819 | 1    |

**Aframax**

| SPOT            | -3.411202 | 14    | 5.00        | -4.211207 | 15    | 3.07        | -5.723804 | 3    | -6.394661 | 3    |
| LogSPOT         | -3.084485 | 12    | 4.87        | -4.077137 | 12    | 3.59        | -4.896919 | 3    | -5.879056 | 4    |
| Timecharter_Rate| -3.361314 | 14    | 4.90        | -3.980898 | 15    | 2.37        | -4.823215 | 2    | -5.346847 | 2    |
| LogTimecharter_Rate| -3.138246 | 12    | 4.97        | -3.900330 | 12    | 2.72        | -3.561784 | 3    | -4.300588 | 4    |

**Panamax**

| SPOT            | -3.835933 | 8     | 6.26        | -5.992611 | 9     | 3.18        | -5.877790 | 5    | -6.637076 | 4    |
| LogSPOT         | -3.183863 | 12    | 5.26        | -4.072439 | 12    | 3.31        | -5.786194 | 1    | -6.704936 | 1    |
| Timecharter_Rate| -2.413106 | 3     | 2.33        | -2.962882 | 4     | 1.67        | -2.381216 | 5    | -2.903565 | 5    |
| LogTimecharter_Rate| -3.648740 | 12    | 7.24        | -6.617425 | 12    | 4.76        | -3.210518 | 5    | -4.564920 | 1    |

**Handysize**

| SPOT            | -4.841871 | 4     | 10.03       | -5.426465 | 5     | 2.95        | -5.746835 | 4    | -6.563017 | 5    |
| LogSPOT         | -2.954724 | 12    | 4.57        | -3.373456 | 12    | 1.52        | -5.410445 | 4    | -6.301460 | 5    |
| Timecharter_Rate| -3.421291 | 15    | 5.16        | -6.057274 | 16    | 2.41        | -4.984660 | 13   | -5.020977 | 13   |
| LogTimecharter_Rate| -3.323653 | 13    | 5.49        | -4.256773 | 13    | 3.63        | -3.307321 | 8    | -3.744744 | 8    |

(Continued)
| Table A1. (Continued) |
|-----------------------|
| **Tankers**           |
| **Unit root tests**   |
| **Ships variables**   |
| **Unit root test**    |
| (constant)—ADF        |
| (constant and trend)—ADF |
| (constant)—PP         |
| (constant and trend)—PP |
| **KPSS**              |
| **F-statistic**       |
| **Critical values**   |
| **Mackinnon critical values** |
| **Shipping variables** |
| **Constant** | Lags | **F-statistic** | Lags | **F-statistic** | Intercept | Lags | Intercept and Trend | Lags | Intercept and Trend | Lags | **Lags** |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Capesize              | -3.009398 | 12 | 2.83 | -3.934291 | 13 | 3.24 | -3.018661 | 15 | -3.806438 | 14 | .191327 | 30 |
| LogSpot               | -2.372179 | 2 | 2.70 | -3.625905 | 2 | 3.25 | -2.538752 | 6 | -3.699099 | 7 | .135861 | 18 |
| Timecharter_Rate     | -3.569842 | 3 | 3.88 | -4.682310 | 12 | 29.44 | -3.215520 | 5 | -3.603720 | 5 | .109682 | 16 |
| Log-Timecharter_Rate | -2.95191  | 1 | 3.96 | -3.505408 | 1 | 1.80 | -3.024795 | 10 | -3.683413 | 10 | .048695 | 17 |
| Panamax_Bulk         | -3.106391 | 7 | 3.51 | -4.946269 | 8 | 1.37 | -2.909847 | 1 | -3.819363 | 1 | .204703 | 30 |
| Log Spot             | -2.574215 | 4 | 3.12 | -3.991097 | 5 | 1.65 | -2.81196 | 3 | -3.808061 | 4 | .111303 | 18 |
| Timecharter_Rate     | -4.049112 | 4 | 4.72 | -4.712969 | 5 | 2.86 | -3.381721 | 1 | -3.837920 | 1 | .117621 | 16 |
| Log-Timecharter_Rate | -3.215271 | 1 | 4.83 | -4.349858 | 1 | 4.22 | -3.050105 | 7 | -3.959188 | 8 | .057740 | 16 |
| Handymax             | -2.951275 | 1 | 2.78 | -4.139906 | 1 | 4.19 | -2.567013 | 3 | -3.586628 | 3 | .215300 | 35 |
| LogSpot_Bulk         | -2.055832 | 1 | 2.21 | -3.602905 | 1 | 4.44 | -2.081199 | 7 | -3.410146 | 7 | .173846 | 17 |
| Timecharter_Rate     | -3.696674 | 11 | 4.20 | -4.883746 | 12 | 5.07 | -3.027410 | 5 | -3.738123 | 5 | .160589 | 30 |

(Continued)
### Table A1. (Continued)

**Bulk Carriers**

| Ships variables | Unit root test (constant)—ADF | Unit root test (constant and trend)—ADF | Unit root test (constant)—PP | Unit root test (constant and trend)—PP | KPSS |
|-----------------|-------------------------------|-----------------------------------------|----------------------------|----------------------------------------|------|
|                 | Constant | Lags | F-statistic | Const./trend | Lags | F-statistic | Intercept | Lags | Interc./trend | Lags | Interc./trend | Lags |
| Log-Timechar-Rate | −2.884710 | 8 | 4.68 | −4.605126 | 9 | 4.98 | −2.563987 | 9 | −3.737337 | 9 | .077196 | 17 |
| Critical values | F-statistic | 4.61 | Critical values | F-statistic | 6.30 | Kwiatkowski-Philips-Schmidt-Shin (1992) |
| Critical values 1% | −3.443719 | −3.977251 | −3.443388 | −3.976781 | .21600 |
| Critical values 5% | −2.867129 | −3.419191 | −2.867183 | −3.418962 | .14600 |
| Critical values 10% | −2.569916 | −3.132165 | −2.569837 | −3.132030 | .11900 |

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.
| 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 | Exogenous |
| Scrap value | Endogenous | Endogenous | Exogenous | Endogenous | Endogenous |
| Fleet capacity | Endogenous | Endogenous | Endogenous | Exogenous | Exogenous |
| % Change of GDP | Exogenous | Exogenous | Exogenous | – | – |
| % Change of seaborne trade | – | – | – | Exogenous | Exogenous |

| Vessels | Tankers |
|---------|---------|
| Capesize | Panamax Bulk | Handymax |
| Spot | Endogenous | Endogenous | Endogenous |
| Timecharter | Exogenous | Exogenous | Exogenous |
| Secondhand Pr. | Exogenous | Exogenous | Endogenous |
| Newbuilding Pr. | Endogenous | Exogenous | 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

| Variable | ULCC-VLCC | Suezmax | Aframax | Panamax | Handysize |
|----------|-----------|---------|---------|---------|-----------|
| Coefficient | C | AR(1) | C | AR(1) | C | AR(1) | C | AR(1) | C | AR(1) |
| 55.69 | .862 | 83.80 | .900 | 111.11 | .881 | 149.10 | .883 | 190.14 | .871 |
| Std. Error | 6.646 | .022 | 10.45 | .019 | 10.779 | .081 | 12.92 | .021 | 14.797 | .128 |
| 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 | X²-statistic (critical value) | ULCC-VLCC | Suezmax | Aframax | Panamax | Handysize |
|------|-------------------------------|-----------|---------|---------|---------|-----------|
| 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 | 38.35 | 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

| Variable | Capesize | Panamax Bulk | Handymax |
|----------|----------|--------------|----------|
| Coefficient | C | AR(1) | C | AR(1) | C | AR(1) |
| 14.28 | .968 | 28.63 | .971 | 28.55 | .983 |
| Std. Error | 4.799 | .011 | 7.804 | .010 | 11.54 | .008 |
| t-statistic | 2.977 | 86.69 | 3.669 | 91.91 | 2.473 | 116.3 |
| Prob. | .0031 | .0000 | .0000 | .0000 | .0137 | .0000 |

**ARCH effect**

| Lags | X²-statistic (critical value) | Capesize | Panamax Bulk | Handymax |
|------|-------------------------------|----------|--------------|----------|
| 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. Diagnostic tests ARMA model—Tankers

| Vessel size | Q-Statistic | Breusch–Godfrey LM test |
|-------------|-------------|-------------------------|
| Tankers     | Qₖ (36)     | X² | Serial correlation (2 lags) | X² |
| 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 model—Bulk carriers

| Bulk carriers | Qₖ (36) | X² | Serial correlation (2 lags) | X² |
|---------------|---------|----|-----------------------------|----|
| 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 |
**Table A7. VAR estimations (Tanker—Bulk carriers)**

**Vector autoregression estimates for D(Spot) ULCC- VLCC (Tankers)**

Sample (adjusted): 1970M06 2011M02—Included observations: 489 after adjustments

| Variables                 | Coeff.  | t-Statistic | Variables                 | Coeff.  | t-Statistic |
|---------------------------|---------|-------------|---------------------------|---------|-------------|
| D(Spot(-1))               | -.0522  | [-2.452]    | D(Secondhand_Pr.(-3))    | -.3579  | [-1.653]    |
| D(Spot(-2))               | -.0498  | [-2.344]    | D(Secondhand_Pr.(-4))    | .0913   | [4.24]      |
| D(Spot(-3))               | -.0008  | [-0.039]    | D(Scrap_Value(-1))       | .2268   | [1.274]     |
| D(Spot(-4))               | -.0410  | [-1.888]    | D(Scrap_Value(-2))       | 2.6092  | [3.052]     |
| D(Newbuilding_Pr.(-1))   | .3316   | [1.208]     | D(Scrap_Value(-3))       | 2.6489  | [3.079]     |
| D(Newbuilding_Pr.(-2))   | .1248   | [.463]      | D(Scrap_Value(-4))       | -1.6244| [-1.915]    |
| D(Newbuilding_Pr.(-3))   | -.2546  | [-.950]     | C                         | -.3343  | [-.589]     |
| D(Newbuilding_Pr.(-4))   | -.2235  | [-.857]     | Percentage_Gdp            | .9234   | [1.865]     |
| D(Secondhand_Pr.(-1))    | -.1166  | [-3.776]    | D(Fleet_Dwt(−1))         | 6.7747  | [2.260]     |
| D(Secondhand_Pr.(-2))    | -.0699  | [-2.259]    | D(Fleet_Dwt(−2))         | .7851   | [.267]      |
| D(Secondhand_Pr.(-3))    | -.0366  | [-1.167]    | D(Fleet_Dwt(−3))         | -1.0906| [-.371]     |
| D(Secondhand_Pr.(-4))    | -.2120  | [-2.480]    | D(Fleet_Dwt(−4))         | -7.0020| [-2.327]    |
| D(Scrap_Value(-1))       | .35168  | [2.106]     | Percentage_Gdp            | 1.3652  | [1.790]     |
| R²                        | .798381 |             | Akaike information criterion | 18.348 |
| S.E. equation             | 10.60739|             | Schwarz criterion         | 19.034 |
| Log likelihood            | -4406.19|             |                           |        |

**Vector autoregression estimates of D(Spot) SUEZMAX (Tankers)**

Sample (adjusted): 1970M06 2011M02—Included observations: 489 after adjustments

| Variables                 | Coeff.  | t-Statistic | Variables                 | Coeff.  | t-Statistic |
|---------------------------|---------|-------------|---------------------------|---------|-------------|
| D(Spot(-1))               | -.1166  | [-1.776]    | 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))    | -.12100 | [-2.480]    | D(Fleet_Dwt(−3))         | -1.0906| [-.371]     |
| D(Secondhand_Pr.(-2))    | -.12898 | [-2.671]    | D(Fleet_Dwt(−4))         | -7.0020| [-2.327]    |
| D(Secondhand_Pr.(-3))    | -.3355  | [-.705]     | C                         | -.8035  | [-.866]     |
| D(Secondhand_Pr.(-4))    | .7383   | [1.561]     | D(Timecharter)           | 4.9022  | [26.32]     |
| 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]     |
| R²                        | .5920   |             | Akaike information criterion | 13.7441|            |
| S.E. equation             | 16.370  |             | Schwarz criterion         | 14.4300|            |
| Log likelihood            | -3280.4|             |                           |        |            |

**Vector autoregression estimates of D(Spot) AFRAMAX (Tankers)**

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

| Variables                 | Coeff.  | t-Statistic | Variables                 | Coeff.  | t-Statistic |
|---------------------------|---------|-------------|---------------------------|---------|-------------|
| D(Spot(-1))               | -.0978  | [-3.104]    | D(Fleet_Dwt(−4))         | 6.8323  | [1.621]     |
| D(Spot(-2))               | -.0925  | [-3.029]    | D(Fleet_Dwt(−5))         | -6.6016| [-1.532]    |
| D(Spot(-3))               | -.0822  | [-2.613]    | D(Fleet_Dwt(−6))         | -1.7867| [-.413]     |
| D(Spot(-4))               | -.0765  | [-2.477]    | C                         | -.6412  | [-.498]     |
| D(Spot(-5))               | -.0319  | [-1.042]    | D(Timecharter_Rate)      | 7.1652  | [22.26]     |
| D(Spot(-6))               | -.0703  | [-2.247]    | D(Secondhand_Pr.)        | .1497   | [.208]      |
| D(Fleet_Dwt(-1))          | 5.1680  | [1.234]     | D(Newbuilding_Pr.)       | 2.5377  | [2.913]     |
| D(Fleet_Dwt(-2))          | -.7321  | [-1.794]    | D(Scrap_Value)            | 1.6467  | [5.92]      |

(Continued)
Table A7. (Continued)

Vector autoregression estimates of D(SPOT) AFRAMAX (Tankers)
Sample (adjusted): 1970M08 2011M02—Included observations: 487 after adjustments

| Variables                  | Coeff. | t-Statistic | Variables                  | Coeff. | t-Statistic |
|----------------------------|--------|-------------|----------------------------|--------|-------------|
| D(Fleet_Dwt(−3))           | 2.8582 | [6.63]      | Percentage_Gdp             | 1.0135 | [1.082]     |
| $R^2$                      | .5839  |             | Akaike information criterion | 8.721014 |             |
| S.E. equation              | 20.185 |             | Schwarz criterion          | 9.030618 |             |
| Log likelihood             | −2087.5|             |                            |        |             |

Vector autoregression estimates of D(SPOT) PANAMAX (Tankers)
Sample (adjusted): 1970M08 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.(−6))    | −.088206 | [−.051]     |
| D(SPOT(−4))                | −.041316 | [−1.059]   | C                          | −2.14986 | [−.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(Scrap_Value)             | 3.098490 | [2.227]     |
| D(Newbuilding_Pr.(−2))    | 1.238302 | [.693]     | D(Fleet_Dwt(−1))           | −14.650 | [1.293]     |
| D(Newbuilding_Pr.(−3))    | −2.471770 | [−1.397]  | Percentage_Seaborne        | .545972 | [.278]      |
| $R^2$                      | .375099 |             | Akaike information criterion | 11.96602 |             |
| S.E. equation              | 29.16946 |             | Schwarz criterion          | 12.27562 |             |
| Log likelihood             | −2877.725 |            |                            |        |             |

Vector autoregression estimates of D(SPOT) HANDYSIZE (Tankers)
Sample (adjusted): 1970M06 2011M02—Included observations: 489 after adjustments

| Variables                  | Coeff. | t-Statistic | Variables                  | Coeff. | t-Statistic |
|----------------------------|--------|-------------|----------------------------|--------|-------------|
| D(Spot_Bulk(−1))          | −.0516 | [−1.254]   | D(Scrap_Value(−3))         | −.5800 | [−.057]     |
| D(Spot_Bulk(−2))          | −.2518 | [−6.121]   | D(Scrap_Value(−4))         | 11.105 | [1.099]     |
| D(Spot_Bulk(−3))          | −.0654 | [−1.578]   | D(Fleet_Dwt(−1))           | 14.650 | [1.293]     |
| D(Spot_Bulk(−4))          | −.0087 | [−208]     | D(Fleet_Dwt(−2))           | −13.105 | [−1.183]    |
| D(Newbuilding_Pr.(−1))   | 2.8106 | [1.025]    | D(Fleet_Dwt(−3))           | −5.467 | [−.048]     |
| D(Newbuilding_Pr.(−2))   | 2.4843 | [.897]     | D(Fleet_Dwt(−4))           | −5.6595 | [−.496]     |
| D(Newbuilding_Pr.(−3))   | −3.4757 | [−1.262]  | C                          | −2.310 | [−.120]     |
| D(Newbuilding_Pr.(−6))   | −3.3492 | [−1.248]  | D(Timecharter)             | 5.5870 | [10.77]     |
| D(Scrap_Value(−1))       | 25.806 | [2.635]    | Percentage_Seaborne        | 2.1800 | [.843]      |
| D(Scrap_Value(−2))       | 2.1378 | [.213]     | D(Secondhand_Pr.)          | −12349 | [−.706]     |
| $R^2$                     | .2762  |             | Akaike information criterion | 10.85258 |             |
| S.E. equation             | 38.854 |             | Schwarz 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]     |

(Continued)
### Table A7. (Continued)

Vector autoregression estimates of D(Spot_Bulk) CAPESIZE (Bulk carriers)

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

| Variables                              | Coeff. | t-Statistic | Coeff. | t-Statistic |
|----------------------------------------|--------|-------------|--------|-------------|
| D(Spot_Bulk(−3))                      | 0.0328 | −1.158      | 0.1603 | 2.480       |
| D(Spot_Bulk(−4))                      | −0.2717| −9.486      | 0.0776 | 0.803       |
| D(Spot_Bulk(−5))                      | 0.1583 | [5.462]     | −0.0727| −0.650      |
| D(Spot_Bulk(−6))                      | −0.0253| −0.926      | 0.7755 | [19.83]     |
| D(Newbuilding_Pr.(−1))                | 0.0099 | [1.48]      | −1.163 | [−1.012]    |
| D(Newbuilding_Pr.(−2))                | −0.0206| −0.302      | 0.1098 | [0.480]     |
| D(Newbuilding_Pr.(−3))                | −0.0454| −0.682      | 0.4164 | [10.02]     |
| R²                                    | 0.7498 |             |        |             |
| S.E. equation                         | 1.7253 |             |        |             |
| Log likelihood                        | −1710.8|             |        |             |

Vector autoregression estimates of D(Spot_Bulk) PANAMAX (Bulk carriers)

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

| Variables                              | Coeff. | t-Statistic | Coeff. | t-Statistic |
|----------------------------------------|--------|-------------|--------|-------------|
| D(Spot_Bulk(−1))                      | 0.0553 | [1.217]     | 0.2392 | [2.089]     |
| D(Spot_Bulk(−2))                      | 0.0426 | [−0.866]    | −1.169 | [−2.13]     |
| D(Spot_Bulk(−3))                      | −0.1719| [−3.513]    | −0.3166| [−0.397]    |
| D(Spot_Bulk(−4))                      | 0.1427 | [2.877]     | 0.0710 | [0.884]     |
| D(Spot_Bulk(−5))                      | −0.0458| [−0.890]    | −1.4265| [−1.694]    |
| D(Spot_Bulk(−6))                      | 0.0278 | [0.539]     | 0.0154 | [0.018]     |
| D(Newbuilding_Pr.(−1))                | 0.5330 | [2.047]     | 0.6425 | [0.794]     |
| D(Newbuilding_Pr.(−2))                | −0.0184| [−0.069]    | 2.6716 | [3.167]     |
| D(Newbuilding_Pr.(−3))                | −0.3299| [−1.232]    | −1.1763| [−2.03]     |
| D(Newbuilding_Pr.(−4))                | −0.6005| [−2.350]    | 0.6515 | [0.765]     |
| D(Newbuilding_Pr.(−5))                | −1.179 | [−4.73]     | 0.0929 | [0.109]     |
| D(Newbuilding_Pr.(−6))                | −1.061 | [−4.40]     | −0.8632| [−1.029]    |
| D(Secondhand_Pr.(−1))                 | 0.0480 | [0.393]     | D(Scrap_Value(−1)) 2.6716 | [3.167]     |
| D(Secondhand_Pr.(−2))                 | 0.2172 | [1.746]     | C 0.3625 | [1.399]     |
| D(Secondhand_Pr.(−3))                 | 0.0688 | [0.547]     | Percentage Seaborne −0.0839 | [−0.343]    |
| D(Secondhand_Pr.(−4))                 | −0.3391| [−2.664]    | D(Timecharter) 1.1785 | [15.64]     |
| D(Secondhand_Pr.(−5))                 | 0.1745 | [1.374]     |        |             |
| R²                                    | 0.4941 |             |        |             |
| S.E. equation                         | 3.5973 |             |        |             |
| 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 | Coeff. | t-Statistic |
|----------------------------------------|--------|-------------|--------|-------------|
| D(Spot_Bulk(−1))                      | 0.0222 | [0.547]     | 0.0948 | [0.873]     |
| D(Spot_Bulk(−2))                      | −0.1853| [−4.447]    | 0.3268 | [3.047]     |
| D(Spot_Bulk(−3))                      | −0.0583| [−1.137]    | 0.3851 | [3.625]     |
| D(Spot_Bulk(−4))                      | −0.1600| [−3.891]    | −0.1831| [−1.726]    |
### Table 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]     | C                    | .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 | [−1.136]    |
| D(Newbuilding_Pr.(−5)) | −.1095 | [−.469]     | D(Fleet_Dwt)        | −.5513 | [−1.405]    |
| D(Newbuilding_Pr.(−6)) | −.2725 | [−1.233]    |                      |        |            |

R²: .6335
S.E. equation: 2.5583
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) | 1.540822  [1.34216] |
| Newbuilding_Pr.(−1) | −5.644820 [−3.87671] |
| Scrap_Value(−1)   | 27.95869   [3.57976] |
| Fleet_Dwt(−1)     | −.573406   [−1.39674] |
| C                 | 180.4849   |

Error Correction:

| Coint. Eq1 | D(SPOT) | D(Secondhand_Prices) | D(Newbuilding_Prices) | D(Scrap_Value) | D(Fleet_Dwt) |
|------------|---------|----------------------|-----------------------|----------------|--------------|
|            | −.003354| .002087              | .004285               | −.000558       | .001798      |
|            | [−.46361]| (1.12219)            | (3.43981)             | [−1.20114]     | (3.64057)    |

R²: .801158
S.E. equation: 10.41086
Log likelihood: −4825.421

Akaike information criterion: 20.53561
Schwarz criterion: 22.04063

### Table A8. VECM estimations (Suezmax—Tankers)

**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] |
| C                 | −32.46050  |

Error Correction:

| Coint. Eq1 | D(SPOT) | D(Secondhand_Prices) | D(Newbuilding_Prices) | D(Scrap_Value) | D(Fleet_Dwt) |
|------------|---------|----------------------|-----------------------|----------------|--------------|
|            |         |                      |                       |                |              |

(Continued)
**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. Eq2 |
|---|---|---|---|
| Coint. Eq1 | −.048016 | −.000395 | .001950 | −.001276 | .000418 |
| \([-3.34101]\) | \([-25.855]\) | \(1.89795\) | \([-2.85593]\) | \(1.91475\) |
| \(R^2\) | .601082 | .172282 | .286858 | .114320 | .277123 |
| S.E. equation | 16.25639 | 1.728756 | 1.162324 | .505564 | .246819 |
| Log likelihood | Akaike information criterion | Schwarz 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 |
|---|---|---|---|
| Coint. Eq1 | .000000 | .000000 | .000000 |
| \(\begin{array}{c} \text{SPOT}(-1) \\ \text{Fleet\_Dwt}(-1) \end{array} \) | \(\begin{array}{c} 1.000000 \\ .000000 \end{array} \) | \(\begin{array}{c} .000636 \\ .003754 \end{array} \) |
| Secondhand\_Prices\((-1)\) | −3.055570 | 11.93197 | \([-4.02398]\) | \(3.37157\) |
| \(\begin{array}{c} \text{C} \\ \text{Error\ correction} \end{array} \) | −26.33813 | −373.9440 | |
| Coint. Eq2 | −.092061 | .000636 | .003754 |
| \(\begin{array}{c} \text{SPOT}(-1) \\ \text{Fleet\_Dwt}(-1) \end{array} \) | \(\begin{array}{c} 1.000000 \\ .000000 \end{array} \) | \(\begin{array}{c} 2.260011 \\ 2.27193 \end{array} \) |
| \(-1.73067\) | \([-2.26001]\) | \(2.37E-05\) | \([.6360]\) |
| \(R^2\) | .603388 | .370946 | .308237 |
| S.E. equation | 19.85839 | .216011 | .1268140 |
| Log likelihood | Akaike information criterion | Schwarz criterion |
| −2855.992 | 12.06157 | 12.75818 |

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

| Sample (adjusted): 1970M06–2011M02—Included observations: 489 after adjustments, t-statistics in [ ] | Cointegrating Eq: | Coint. Eq1 | Coint. Eq2 |
|---|---|---|---|
| Coint. Eq1 | .000000 | .000000 | .000000 |
| \(\begin{array}{c} \text{SPOT}(-1) \\ \text{Newbuilding\_Prices}(-1) \\ \text{Fleet\_Dwt}(-1) \end{array} \) | \(\begin{array}{c} 1.000000 \\ .000000 \\ 5.255168 \end{array} \) | \(\begin{array}{c} .001189 \\ .000281 \\ .002103 \end{array} \) |
| \(\begin{array}{c} \text{C} \\ \text{Error\ correction} \end{array} \) | −237.7539 | −49.42429 | |
| Coint. Eq2 | −.216999 | .001189 | .000281 |
| \(\begin{array}{c} \text{SPOT}(-1) \\ \text{Newbuilding\_Prices}(-1) \\ \text{Fleet\_Dwt}(-1) \end{array} \) | \(\begin{array}{c} 1.000000 \\ .000000 \\ 5.255168 \end{array} \) | \(\begin{array}{c} .163786 \\ .269427 \end{array} \) |
| \(\begin{array}{c} \text{C} \\ \text{Error\ correction} \end{array} \) | −237.7539 | −49.42429 | |
| \(-.010109\) | \([-7.98795]\) | \(2.69427\) | \(2.69427\) |
| \(R^2\) | .603388 | .370946 | .308237 |
| S.E. equation | 19.85839 | .216011 | .1268140 |
| Log likelihood | Akaike information criterion | Schwarz criterion |
| −2855.992 | 12.06157 | 12.75818 |

(Continued)
### 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] |
| C                   | −34.48705  |       |

Error correction:

| Coint. Eq1 | D(SPOT) | D(Newbuilding_Prices) | D(Scrap_Value) |
|------------|---------|-----------------------|----------------|
| −.147034   | .002438 | −.000357              |                |
| (−4.42416) | (4.34322)| (−2.17613)            |                |

R²: 

|       | .316044 | .230622 | .056724 |
|-------|---------|---------|---------|

S.E. equation:

|       | 37.48330| .633099 | .185136 |
|-------|---------|---------|---------|

Log likelihood

|       | −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) |
| C                   | 31.27048   |       |

Error correction:

| Coint. Eq1 | D(Spot_Bulk) | D(Newbuilding_Prices) |
|------------|--------------|-----------------------|
| −.025728   | .022566      |                       |
| (−2.45942) | (3.16150)    |                       |

R²: 

|       | .752692 | .305278 |
|-------|---------|---------|

S.E. equation:

|       | 1.717535| 1.171876 |
|-------|---------|----------|

Log likelihood

|       | −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   |
| C                   | 25.35444   | 18.41539   | −368095    | −76.77063  |

Error correction:

| Coint. Eq1 | D(Spot_Bulk) | D(Secondhand_Prices) | D(Newbuilding_Prices) | D(Fleet_Dwt) | D(Scrap_Value) |
|------------|--------------|----------------------|-----------------------|--------------|----------------|
| −.083451   | .010823      | .003753              | .003252               | .005962      |
| (−2.86145) | (.88385)     | (.70622)             | (1.91473)             | (3.25534)    |
| .059989    | −.079856     | .004048              | −.006101              | −.003896     |

(Continued)
## 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          | −0.038739        | .003048          | −.004132         |
|                   | (2.10746)        | (2.02456)        | (−3.41006)       | (0.83974)        | (−1.05545)       |
| Coint. Eq4        | .012148          | −.004285         | −0.003120        | .001291          | .000112          |
|                   | (1.65662)        | (−1.39167)       | (−2.33473)       | (3.02216)        | (2.24233)        |
| \( R^2 \)         | 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       |
|-------------------|------------------|------------------|------------------|
|                   | 1.000000         | .000000          | .000000          |
| Spot_Bulk(−1)     | .000000          | 1.000000         | .000000          |
| Secondhand_Prices(−1) | .000000       | .000000          | 1.000000         |
| Newbuilding_Prices(−1) | .000000      | .000000          | 1.000000         |
| Fleet_Dwt(−1)     | 3.235324         | 1.582158         | 1.384436         |
|                   | (2.55074)        | (2.24684)        | (2.74668)        |
| \( C \)           | −148.8089        | −78.34988        | −77.46503        |
| Error Correction: | D(Spot_Bulk)     | D(Secondhand_Prices) | D(Newbuilding_Prices) | D(Fleet_Dwt) |
|                   | D(Spot_Bulk)     | D(Secondhand_Prices) | D(Newbuilding_Prices) | D(Fleet_Dwt) |
| Coint. Eq1        | −.020136         | .004040          | .008559          | .003310         |
|                   | (−1.22390)       | (1.65017)        | (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)       |
| \( R^2 \)         | .646993          | .734067          | .438884          | .777903         |
| S.E. equation     | 2.532805         | .956279          | .501127          | .146245         |
| Log likelihood    | Akaike information criterion | Schwarz criterion |
| −1842.059         | 8.123444         | 9.293062         |
## Table A9. ARMA estimations

### ARMA models

| Estimated parameter | Sample period | Dependent variable | 1970:01–2011:02 |
|---------------------|---------------|--------------------|----------------|
|                     |               | 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 |
| C                   |               | 50.51440 (7.289256) | 84.35932 (7.766115) | 109.7379 (8.757144) | 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 (3.642646) | −.676455 (−6.633687) | .670766 (8.249042) | .953212 (19.96283) |
| AR(2)               |               | −.570836 (−10.07574) | −.177158 (−3.585934) | −.186717 (−4.195846) | −.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) | .651510 (10.73098) |                     |                     |
| AR(5)               |               | .821065 (27.48851) | .157016 (3.245630) | −.203068 (−3.516742) | −.147111 (−2.651800) |                     |                     |                     |                     |
| AR(6)               |               |                     |                     |                     |                     |                     |                     |                     |                     |
| 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 (3.761995) | .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 (9.345499) | .110482 (25.47100) | 1.072774 (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

| Sample period | 1970:01–2011:02 |
|---------------|-----------------|
| Estimated 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 |
| C | 5.691304 (2.213809) | 6.466746 (2.867686) | 17.89197 (2.199346) | 108.3865 (3.505629) | 139.9965 (3.156653) | 0.028021 (3.400383) | 0.106843 (3.561445) | 0.102673 (3.375823) |
| ARCH (1) | 0.392118 (12.32730) | 0.455110 (9.027228) | 0.211607 (8.028785) | 0.245802 (6.067745) | 0.241939 (12.68916) | 0.462388 (7.730518) | 0.184306 (3.519282) | 0.340177 (7.806101) |
| ARCH (2) | 0.444280 (10.53461) | -0.262658 (-4.535314) | 0.210654 (8.342708) | -0.237916 (-5.166334) | 0.224924 (7.449137) | -0.360060 (-3.151224) | -0.172317 (-2.215224) |
| ARCH (3) | 0.337736 (9.539731) | 0.296729 (6.757749) | 0.205676 (7.318297) | 0.239949 (6.312831) | 0.182055 (9.40213) | 0.212833 (3.373868) | 0.134430 (2.810678) |
| ARCH (4) | 0.225983 (8.482686) | 0.246055 (6.054769) | 0.202829 (9.19500) |
| GARCH (1) | -0.195273 (-3.900444) | 0.731743 (25.29878) | -0.082794 (-2.620347) | -0.128263 (-2.849323) | -0.328229 (-9.388411) | 1.563985 (23.15113) | 2.024000 (135.6112) | 0.992152 (7.109913) |
| GARCH (2) | -0.127651 (-3.358435) | -0.629088 (-19.46479) | -0.248008 (-7.881385) | -0.180311 (-5.838934) | -0.141188 (-6.193502) | -1.321975 (-21.73843) | -1.881301 (-47.80925) | -0.581392 (-3.200924) |
| GARCH (3) | 0.493274 (10.55966) | 0.493006 (22.84013) | -0.197958 (-7.981229) | -0.335436 (-11.11069) | -0.096629 (-4.260191) | 0.506914 (20.39618) | 0.717883 (41.94791) | 0.297335 (3.182537) |
| GARCH (4) | 0.811815 (30.57328) | 0.696045 (19.24948) | 0.731271 (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 | 9.511045 | 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

| Sample period | 1970:01–2011:02 |
|---------------|-----------------|
| Estimated 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 |
| C | 0.800997 (1.154514) | 0.189936 (2.655860) | 0.174026 (2.254872) | 0.122143 (1.537995) | 0.210860 (2.895870) | -0.112579 (-2.516638) | -0.113772 (-3.472137) | -0.144885 (-3.930217) |
| ARCH (1) | 0.173862 (2.711991) | 0.079576 (1.292355) | 0.131530 (2.105265) | -0.055893 (-2.901913) | 0.112892 (2.607516) | 0.211706 (4.574134) | 0.209561 (4.351464) |
| GARCH (1) | 0.949529 (85.63437) | 0.950800 (70.29388) | 0.952892 (84.38945) | 0.963117 (80.57513) | 1.153938 (439.2297) | 0.468422 (5.440948) | 1.030720 (18.77174) | 0.697731 (9.252560) |
| GARCH (2) | -0.517418 (-26.98499) | -0.393596 (-5.740468) | -0.167527 (-2.810100) | -0.851964 (10.64576) |
| GARCH (3) | 0.779859 (38.02508) | 0.125720 (1.530027) | 0.181747 (4.066184) | -0.119865 (-8.040732) |
| GARCH (4) | -0.446274 (-128.7171) | -0.328864 (-9.664393) | 0.661886 (5.539970) | (Continued)
### Table A11 (Continued)

**E-GARCH models**

| Sample period | Estimated parameter | Dependent variable |
|---------------|---------------------|--------------------|
|               | Deseason spot U-VLCC | 1970:01–2011:02    |
|               | Deseason spot Suezmax|
|               | Deseason spot Aframax|
|               | Deseason spot Panamax|
|               | Deseason spot Handysize|
|               | 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 Parameter | 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)  | 1.421111 (11.22765)  |
|               | 1.365070 (7.176910)  | .462934 (9.851868)   |
|               | .326644 (6.575959)   | .338859 (7.615534)   |
|               | .290796 (9.314992)   | .526844 (10.81342)   |
|               | .140141 (4.630916)   | .187258 (5.892187)   |
|               | 7.578090 8.061229    | 8.642392 9.267484    |
|               | 9.798426 2.929507    | 4.470121 3.922165    |
|               | 7.637732 8.120871    | 8.710554 9.327126    |
|               | 9.892150 3.014710    | 4.580885 4.032929    |
|               | 1.985217 1.986143    | 1.910441 1.814212    |
|               | 1.977502 1.253481    | 1.538184 1.266462    |

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