SPOUDAI Journal of Economics and Business, Vol.64 (2014), Issue 2, pp. 14-39

University of Piraeus

SPOUDAI
Journal of Economics and Business
Σπουδαί
http://spoudai.unipi.gr

Ex-Post and Ex-Ante Forecasts of Spot Prices in Bulk Shipping in a Period of Economic Crisis using Simultaneous Equation Models

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Abstract

The paper deals with forecasting of spot prices in bulk shipping using simultaneous equations models (SEMs) during the present economic crisis, emphasizing the importance of such models in empirical applied economics and for decision-makers. The SEMs predictive performance on the spot market is estimated for a selection of eight main vessel categories, five in the tanker market and three in the dry bulk market. SEMs take into account feedback loops between the spot market and its environment. SEMs are considered more complete models as spot prices and variables such as time-charter rates, fleet deadweight capacity and prices of second-hand, newbuilding and scrap markets are determined simultaneously by the shipping markets' operation. This approach enables estimating 29 different systems for each vessel type, generated by the combination of the aforementioned variables. The research sample period consists of an initialization data subset (1970:01-2010:02), of a subset for ex-post forecast (2010:03-2011:02) and a subset for ex-ante forecasts (2011:03-2012:02) employing monthly time series. Results reveal that simultaneous estimation of endogenous variables is described by precision and rationality while the t-tests show that exogenous variables are characterized by very high statistical significance. The out-of-sample forecasts show that SEMs provide useful information about market turning points.

JEL Classification: C530; C320; E32.

Keywords: econometric methodology; simultaneous equations models; spot prices; ex-post and ex-ante forecasts; forecasting uncertainty.

1. Introduction

Econometrics provides the appropriate methodology to investigate the intense volatility of shipping freight rates, a significant feature of the spot market. New econometric techniques solve many methodological problems and econometricians and economists can obtain more efficient and consistent estimations to have more reliable results. A correct and an accurate econometric methodology in the spot market can be a useful tool for the evaluation of alternative policies and for the implementation of efficient decision policies. In this paper, ex-post and ex-ante forecasts are used as out-of-sample forecasts. Ex-post forecasts are used as an evaluating tool to test the precision and the accuracy of the forecasted series versus the actual series. If ex-post forecasts produce small forecasting errors, this is an indication of the correct specification of the adopted econometric model. Therefore, the model can be used for entirely new future forecasts through ex-ante forecasts where there are no actual data. Ex-ante forecasts are one of the most valuable tools for economists and decision-makers as they can justify quantitatively their potential economic policies (Pindyck and Rubinfeld 1998, pp.384).

In very competitive markets like the shipping industry, ex-post and ex-ante forecasts have a primary role to play, particularly in the spot market. The latter reflects the real image of shipping industry because it has a very dynamic mechanism. The spot market brings together both sides of the industry, i.e. shipowners and charterers where every part depends upon their own and others' entrepreneurial activity, which results in market profits or losses. It is obvious that the spot market is influenced by a number of variables, which are related to the internal and the external environments of shipping industry.

This research investigates which variables affect the spot market of the tanker and dry bulk shipping markets using SEMs following a disaggregated analysis. Five and three vessel types are analysed in the tanker and bulk carrier markets respectively. The choice of variables included in each SEM equation is based on the statistical significance they present in the corresponding single equation multiple regression models. The choice of SEMs rests upon the creation of structural equations, which gives the opportunity to identify the appropriate endogenous and exogenous variables which affect each vessel type (Pindyck and Rubinfeld 1998, pp. 340)[1]. In addition, the paper focuses on the estimation of dynamic multipliers and dynamic elasticities, which can be used for the analysis of dynamic responses of shipping variables in relation to other exogenous variables.

The dichotomy between endogenous and exogenous variables is based on exogeneity and identification issues. Spot prices, as the examinant variable, are the first endogenous variable. The other endogenous variables, which are related to spot prices, are determined by conducting the Hausman test for exogeneity (Appendix-Table A1). In addition, the identification procedure, via the satisfaction of order and rank conditions, is closely related to the problem of estimating the structural parameters in SEMs. Thus, when an equation is not identified, such estimation is not possible (Asteriou and Hall, 2007). This procedure leads to the reformation of structural equations inserting or avoiding some predetermined and exogenous variables according to the results of our research.

The advantage of SEMs is that their equations can embody the shipping economic theory when compared to other multiple equation systems models (VAR, VECM); moreover, the method prevails over multiple regressions because the interrelationship among the variables produces better forecasts (Geomelos, 2012).

The paper is structured as follows. The next section presents a brief examination of the previous work on forecasting spot markets with multiple equations. The third section presents the methodology followed, models, variables and data sources. The fourth section analyses the results of SEMs and shows the results of ex-post and ex-

[1] Structural equations incorporate the variables that should be related to one another in a relationship of simultaneity. A structural model, which contains the structural equations, contains the endogenous variables on the left-hand side and exogenous and predetermined variables on the right-hand side (Brook, 2008).

ante forecasts. Finally, the fifth section presents the conclusions of the empirical estimations

2. Literature Review

Historically, few papers have examined SEMs and their application in the shipping, especially in the spot market. The use of SEMs demands extensive research of endogenous and exogenous variables. One of the first shipping studies that uses indirectly system of equations, is that of Tinbergen (1931). Tinbergen created three different equations, where he noticed the evolution of the fleet using the freight rates, the order book and the existing fleet for given values of exogenous variables. Then, he built a type of multiple equations system where he only used the previous variables as endogenous and no exogenous variable. This system was not only used to model the shipping markets but also to produce forecasts.

An important econometric study was performed by Hawdon (1978), where reduced form equations with endogenous and exogenous variables, dummy variables and variables with lags were used for the first time in shipping market modeling. Hawdon’s model was based on the interaction of demand and supply, which are short-term price inelastic to spot rates. Hawdon claimed that in the long-term, the supply is affected by present and expected values of spot prices and the demand is likely to be dependent on freight rate expectations and on the expected volume of world oil trades. One very important econometric remark is that Hawdon used his models not only to interpret the shipping markets, but also to produce simulations or forecasts specifying one of the major goals of econometric research.

Charemza and Gronicki (1981) developed a disequilibrium model for both tanker and dry bulk markets involving three types of equations, one equation for demand, another for supply and the last one for spot prices. Although their equations were not estimated simultaneously, their methodology is based on the discrimination of variables in endogenous and exogenous, which are included in each equation. Charemza and Gronicki used ordinary least-squares (OLS) as a solution method and not the appropriate method of instrumental variables to estimate structural equations separately and not simultaneously. Estimated equations are separated into three categories. The first category includes nominal short-run spot prices, which are determined negatively by the spot prices expectations. The second category includes real short-run spot rates, which use first’s category equations with deflated variables. The third category includes long-run spot rates that are determined positively by cost factors and differentiate spot prices according to their time duration. Charemza and Gronicki’s econometric analysis resulted in a framework to operate three shipping markets, namely the spot market, the new-buildings market and the scrap market.

New econometric techniques led economists to develop new models in the area of multiple equation systems. SEMs were replaced by other econometric models like the vector autoregressive (VAR), vector error correction models (VECM), Autoregressive Moving Average (ARMA) univariate models and Generalized Autoregressive Conditional Heteroskedasticity (GARCH). However, these models have a significant drawback as they cannot include economic theory in their methodology. These models make minimal theoretical demands on the structure of a model and they are used only for forecasting procedures overlooking the theory of shipping market.

After many years, shipping market research using a system of equations emerged againg through the work of Randers and Goluke (2007). They created an interpretation total model of the tanker market without any vessel size or shipping routes discrimination. They built their model according to the total fleet capacity and the way of utilising of this capacity. According to their work, the cyclicality and volatility of he shipping market are not exogenous but endogenous since they result from the market itself. They concluded that if the shipping market acted according to the available information on ordering, scrapping and utilization, it could avoid the intense volatility of spot prices.

3. Methodology

This section presents a theoretical analysis of SEMs methods, which apply to the spot tanker and dry bulk markets. More specifically, it discusses the principles and concepts, associated with the quantitative forecasting techniques of SEMs. The comparative advantage of SEMs against other models, the endogeneity and exogeneity issues, the dynamic behaviour of SEMs, the specification, the identification and the estimation method are presented in the next paragraphs. In addition, the final paragraphs of this section present the research sample period, the used databases and the examinant variables.

3.1 Simultaneous Equations Models

SEMs compose a dynamic mechanism of feedback effects among the endogenous variables and they constitute one of the most appreciable developments of econometrics in terms of estimation and joint endogeneity. Developments in both identification and estimation of SEMs arise from the jointly endogenous feature of economic variables, which are treated from theoretical or statistical viewpoints. The simultaneously determined equations provide the advantage of direct examination of endogenous variables as well as of the observation of feedback effects that exist between the endogenous and the exogenous variables. The most important point in using SEMs is that each equation in the system should have a ceteris paribus, causal interpretation (Wooldridge 2002).

A very important aspect of these models is the implications of the variables joint endogeneity as claimed by Hausman (1983). The endogeneity gives SEMs their unique characteristic, which distinguishes them from most regression type models in statistics. An important form of endogeneity of explanatory variables is simultaneity, which occurs when explanatory variables are jointly determined with the dependent variable, typically through an equilibrium mechanism. Nevertheless, simultaneity can cause ordinary least squares parameter estimators to be inconsistent and an alternative estimation must be used. The leading and more precise method for estimating SEMs and to replace the ordinary least squares parameter estimators is the instrumental variables estimation technique (Wooldridge 2002). The instrumental variables estimation technique is reasonable in the context of SEMs because the predetermined variables in the model serve as excellent instrumental variables.

Another important characteristic of SEMs is their dynamic behaviour, which explains the cyclical market phenomena that occur in the shipping industry. These models are also used to study the short-run and the long-run responses of one variable to another one (Pindyck and Rubinfeld 1998). For example, it is useful to know how the new fleet capacity changes the freight level, but the most important is to determine the time where this change would happen during the examination of the dynamic time lags.

The standard specification of a multiple equation system is according to the theory of matrix (Theil, 1971) as follows:

$$\mathrm{B}\mathrm{y}_i + \Gamma \mathrm{x}_i = \mathrm{k}_i, \quad (1)$$

where,

$$\mathrm{y}_i = \begin{bmatrix} \mathrm{y}_{1i} \\ \mathrm{y}_{2i} \\ \dots \\ \mathrm{y}_{Gi} \end{bmatrix}, \; x_i = \begin{bmatrix} x_{1i} \\ x_{2i} \\ \dots \\ x_{Ki} \end{bmatrix}, \; u_i = \begin{bmatrix} u_{1i} \\ u_{2i} \\ \dots \\ u_{Gi} \end{bmatrix}, \; B = \begin{bmatrix} \beta_{11}, \beta_{12} \dots \beta_{1G} \\ \beta_{21}, \beta_{22} \dots \beta_{2G} \\ \dots\dots\dots \\ \beta_{G1}, \beta_{G2} \dots \beta_{GG} \end{bmatrix}, \; \Gamma = \begin{bmatrix} \gamma_{11}, \gamma_{12} \dots \gamma_{1K} \\ \gamma_{21}, \gamma_{22} \dots \gamma_{2K} \\ \dots\dots\dots \\ \gamma_{G1}, \gamma_{G2} \dots \gamma_{GK} \end{bmatrix}$$

y_i = G x 1 vector of endogenous variables
x_i = K x 1 vector of predetermined variables
u_i = G x 1 vector of disturbance terms
B = G x G matrix of endogenous variables coefficients
Γ = G x K matrix of predetermined variables coefficients
G = endogenous variables
K = predetermined variables

The step that follows during the creation of SEMs is the correct selection of variables, which are to be included in the equations according to the shipping theory. Next, the econometrician must give special attention to differentiate variables as endogenous and exogenous since the final purpose of the employed models is to forecast spot rates in bulk shipping. Each structural equation is determined according to economical hypotheses and statistical tests (t-statistics, DW test, stationarity) as suggested by Heij et al. (2004).

3.2 Identification problem

The identification problem refers to the possibility or not to estimate the parameters of structural equations from the reduced form coefficients. Identification is an important condition for the correct estimation of the variables' parameters and not for the solution of the systems' equations. The estimation problem is created from the fact that the relation of causal interrelation is determined in both directions and the least squares method gives biased and inconsistent parameters resulting in the violation of the independency hypothesis. This problem is known as simultaneous equation bias. There are two conditions required for an equation to be identified, a) the order condition and b) the rank condition.

The selection of instrumental variables as a solution method is crucial to avoid the identification problem and simultaneous equation bias. Every variable, which is exogenous and independent from the disturbance term, can be used as instrumental variable. The variables with time-lags can be also used as instrumental variables in dynamic analysis. As a result, the number of instrumental variables is not specific. However, the main result is that when the number of instrumental variables is increased then the asymptotic efficiency and the simultaneous equation bias are increased too. During the diagnostic test, all conditions are satisfied for all categories of tankers and dry bulk vessels.

3.3 Estimation method- Generalized Method of Moments

The estimation of a multiple equations system is more complicated relatively to single-equation models. If one equation of the system has specification errors then it is possible that all system's equations lead to inconsistent estimations. This outcome results from the fact that the reduced form equations express every endogenous variable as a function of the structural residuals of the rest of the equations (Johnston, DiNardo 2004[2]).

In the paper, estimation of SEMs follows the General Method of Moments (GMM). The use of GMM's parameters is one of the most important econometrical developments and it helps the research and the study of macroeconomic and microeconomic phenomenona (Hansen 1982). GMM is associated closely with the use of instrumental variables. More specifically, when the hypothesis of independency is violated between the disturbance term and explanatory variables then the consistency of estimations comes from the method of instrumental variables.

In this research, we estimate 29 different SEMs and we compare their ex-post forecasts. The SEM with the lowest forecasting errors (lower values of RMSE and Theil) is preferred among the others. The 29 SEMs are coming from the all the possible combinations of spot prices with the main shipping variables (fleet capacity, time-charter rates, second-hand prices and newbuilding prices). In this paper, only the best forecasting SEM is presented for each vessel type in the results' section.

The 29 different SEMs are shown in Table 1.

[2] This means that the endogenous variables can be treated as explanatory variables in structural equations as they related to the disturbance term of structural equation. For this reason OLS is an inappropriate solution method, because it gives inconsistent and biased results (Johnston, DiNardo 2004, pp.307). GMM with the appropriate selection of instrumental variables can provide consistent and unbiased estimations instead of OLS.

Table 1. SEMs equations

Simultaneous Equations Models						
1	Spot	Fleet				
2	Spot	Time-charter				
3	Spot	Second-hand				
4	Spot	Newbuilding				
5	Spot	Scrap				
6	Spot	Fleet	Time-charter			
7	Spot	Fleet	Second-hand			
8	Spot	Fleet	Newbuilding			
9	Spot	Fleet	Scrap			
10	Spot	Time-charter	Second-hand			
11	Spot	Time-charter	Newbuilding			
12	Spot	Time-charter	Scrap			
13	Spot	Second-hand	Newbuilding			
14	Spot	Second-hand	Scrap			
15	Spot	Newbuilding	Scrap			
16	Spot	Fleet	Time-charter	Second-hand		
17	Spot	Fleet	Time-charter	Newbuilding		
18	Spot	Fleet	Time-charter	Scrap		
19	Spot	Fleet	Second-hand	Newbuilding		
20	Spot	Fleet	Second-hand	Scrap		
21	Spot	Fleet	Newbuilding	Scrap		
22	Spot	Fleet	Time-charter	Second-hand	Newbuilding	
23	Spot	Fleet	Time-charter	Second-hand	Scrap	
24	Spot	Fleet	Time-charter	Second-hand	Newbuilding	Scrap
25	Spot	Fleet	Second-hand	Newbuilding	Scrap	
26	Spot	Time-charter	Second-hand	Newbuilding		
27	Spot	Time-charter	Second-hand	Scrap		
28	Spot	Time-charter	Second-hand	Newbuilding	Scrap	
29	Spot	Second-hand	Newbuilding	Scrap		

3.4 Evaluation

A useful criterion that is used to evaluate a SEM is the fit of the actual data in a simulation context. The results of historical simulations must track the behaviour of the real economic world rather closely. Another important criterion to evaluate the forecasts is how well the model simulates turning points in the data (Pindyck and Rubinfeld, 1998). In other words, we evaluate how closely spot prices, as endogenous variables, track the historical data constructing the appropriate figures of ex-post dynamic and static forecasts. In addition to the figures of ex-post forecasts, quantitative criteria have been used to measure how closely spot prices track the actual data. These criteria are Root Mean Simulation Error (RMSE) and Theil's Inequality coefficient.

3.5 Data

The research sample period is based on monthly time-series comprising 494 observations, from January 1970 to February 2011. It is important to notice the use of such a large sample in SEMs, because in sub-samples there are different conclusions, affected by the phase of shipping cycle. A larger sample leads to more general conclusions about the variables that affect spot prices diachronically.

Data was obtained from the Clarksons Research Shipping Intelligent Network internet database. However, for certain time series data used derives from diagrams or tables from the database of Houlder H. and Partners[3]. The categorisation of the tanker and of the dry bulk ships was performed according to their deadweight in the categories presented in Table 2.

Table 2. Categorization of vessels according to their deadweight

Tankers	Dry Bulk Carriers
1. ULCC – VLCC (200,000 dwt +)	1. Capesize (80,000 dwt +)
2. Suezmax (120,000–199,999 dwt)	2. Panamax Bulk (50,000-79,999dwt)
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).	

Six dummy variables are used, in order for each one to declare the existence or not of a situation[4]. Dummy variables are those of war conflict, introduction of new regulations (Erika and Prestige packages)[5], oil pipeline closures, economic crisis, oil crisis and order of new ships. The remaining used variables were separated in shipping and macroeconomic variables presented in Table 3.

The connection of macroeconomic with shipping variables is usual practice in econometric interpretation of shipping phenomena and has been used in several works, as Beenstock and Vergottis (1993), Conrad et al. (1991) and Stopford (1997). For the prices of exchange rate of $/¥ the database given by the website stlouisfed.org was used. For the rate of LIBOR (London Interbank Offered rate 3-month) this paper used data provided by the website economagic.com/blsint.htm. For the rates of crude oil, the index WTI was used.

[3] For these data and diagrams, see Glen et al (1981).

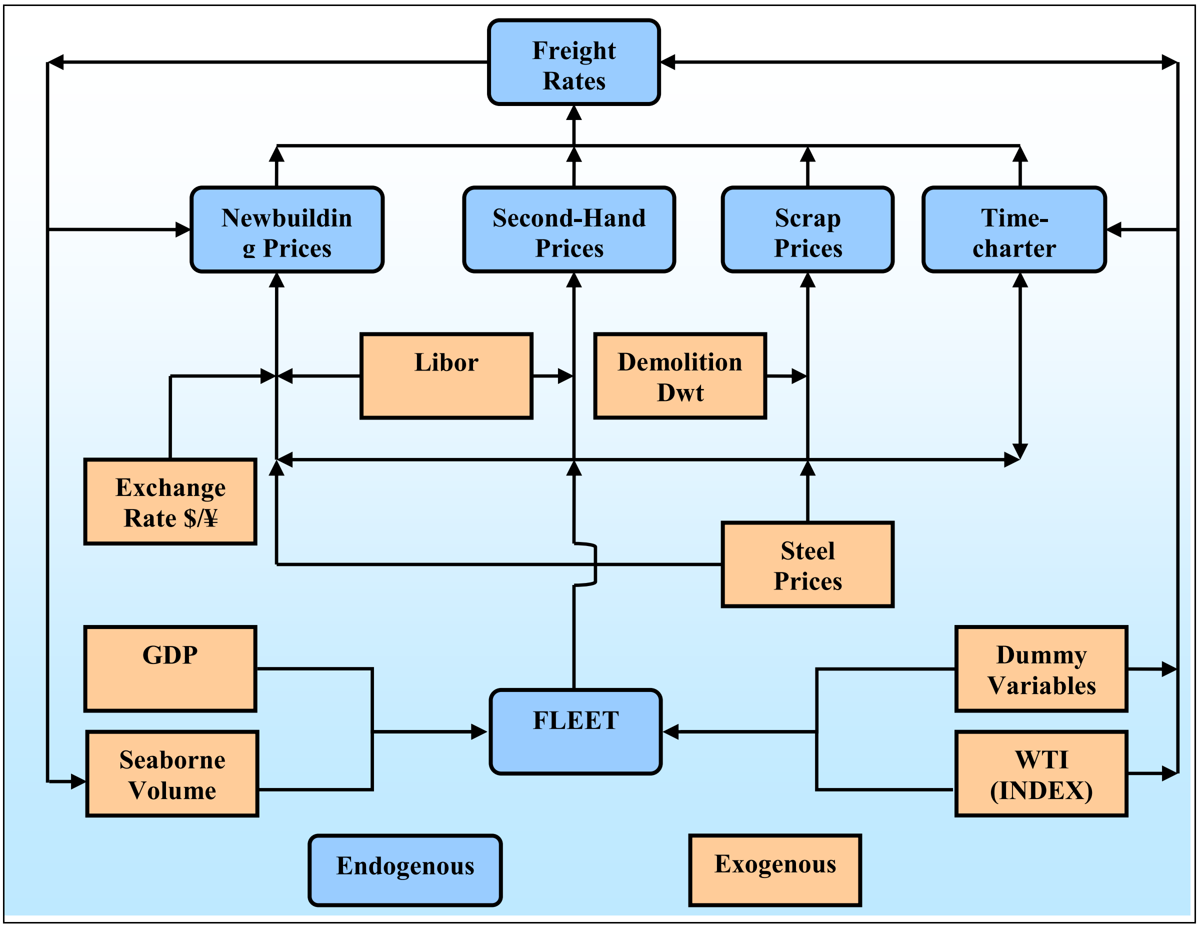
[4] Dummy variables are used to evaluate whether a condition affects spot prices or not. For example, it is not possible to examine quantitatively the impact of the oil or economic crisie. For the months, where an acute oil crisis was present (1973:01- 1974:03, 1979:04-1980:05, 2007:06-2008:10), the variable takes on the value of 1 and 0 if no acute oil crisis existed. In the same way, we put 1 in the following dates of the dummy variables for the economic crisis (1981:01-1981:12, 1992:01-1992:12, 2007:06-2011:02), for the orderbook of new vessels (1973:01-1974:12, 1988:01-1991:12, 2001:01-2005:12), war conflict (1973:10-1973:12, 1980:09-1988:03, 1990:08-1991:02, 2003:03-2003:07), pipeline closure (1970:05-1970:12, 1978:10-1978:12, 1982:03-1982:05), new regulation (1989:03-1990:12, 1999:12-2001:12, 2002:11-2004:10). All dates are based on Stopford (1997) analysis of shipping market cycles.

[5] Erika and Prestige accidents led IMO (International Maritime Organization) to adopt a revised phase-out schedule for single hull oil tankers having as a result the reduction of existing fleet capacity (increase of scrapping vessels and ordering newbuildings), affecting at the same time the level of spot prices.

Table 3. Shipping and Macroeconomic Variables

Shipping Variables	Macroeconomic Variables
• Spot rates (WS)	• Seaborne trade (million tones)
• Time-charter rate ($/day)	• Exchange rate $/¥
• Second-hand prices (5-year old) ($ million)	• 3-month Libor interest
• Fleet capacity (million dwt)	• Bunker Prices ($/ton)
• Newbuilding prices ($ million)	• Worldwide GDP
• Scrap Prices ($/ldt)	• Steel Prices $/ton
• Ship Deliveries and Demolition (million dwt)	• WTI index (West Texas Intermediate)

Figure 1. Flowchart of endogenous and exogenous variables for SEMs



Source: Author

The flowchart in Figure 1, provides a blueprint for the specification of the SEMs. Freight rates are disaggregated into endogenous components that include time-charter rates, second-hand prices, newbuilding prices, scrap prices and fleet deadweight capacity. The remaining components- steel prices, seaborne trade volume, GDP, WTI, exchange rate $/¥, demolition dwt, LIBOR and six dummy variables- are treated as exogenous variables. Each exogenous variable affects the corresponding endogenous variable the way the arrows indicate in the Figure 1. In addition, the figure shows the interdependencies and the feedback effects between the endogenous variables.

4. Estimation results

In this section, results of SEMs' estimations are presented. For each market, the structural equations, which compromise the SEM with the best forecast among the examinant 29 SEMs, are presented analytically with the correspondent dynamic multipliers. In addition, ex-post (dynamic and static) forecasts are performed to evaluate the models' ability to replicate the actual data. For each ex-post forecast, RMSE and Theil coefficients are estimated. Next, we demonstrate the use of estimated models in performing forecasting and in decision making by generating ex-ante forecasts.

4.1 Tanker market

4.1.1 ULCC-VLCC

After the examination of 29 different SEMs, the multiple equation system with the smallest forecasting errors is that with endogenous variables the examinant variable of spot rates, the second-hand prices and newbuilding prices (Table 4). More specifically the equations are as follows:

Log(SPOT)= 1,69 – 0,07*Log(SPOT(-6)) + 0,89*Log(Timecharter_Rate) + 0,07* Percentage_Gdp + 0,18*Dum_Pipe_Close + [AR(1)=0,77] (2)

Dlog(Secondhand_Prices)= -0,04+ 0,14*Dlog(Secondhand_Prices(-2)) + 0,012*Log(SPOT) + [AR(1)=0,14] (3)

Dlog(Newbuilding_Prices)= -0,01+ 0,17*Dlog(Newbuilding_Prices(-2)) + 0,07*Dlog(Secondhand_Prices(-1))+ 0,04*Log(SPOT(-3)) + 0,03*Dlog(Libor)- 0,07*Dlog(Exchange_Rates)+0,15*Dlog(Steel_Pr.)+0,03*Dlog(Scrap_Value(-1)) (4)

Table 4. SEM estimation and Diagnostic Tests (ULCC-VLCC)

Estimation Method: Generalized Method of Moments				
Included observations: 489 - Total system (unbalanced) observations 1463				
Convergence achieved after: 1 weight matrix, 9 total coef iterations				
Variables	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C(1)-Constant Term	1.696923	0.182302	9.308307	0.0000
Log(SPOT(-6))	-0.066273	0.021460	-3.088197	0.0021
Log(Timecharter_Rate)	0.886737	0.053101	16.69902	0.0000
Percentage_Gdp	0.067110	0.039181	1.712837	0.0870
Dum_Pipe_Close	0.178766	0.057469	3.110660	0.0019
AR(1)	0.768422	0.040473	18.98598	0.0000
C(7)-Constant Term	-0.043457	0.018774	-2.314794	0.0208
Dlog(Secondhand_Prices(-2))	0.135618	0.046791	2.898385	0.0038
Log(SPOT)	0.012293	0.004583	2.682299	0.0074
AR(1)	0.140643	0.040524	3.470588	0.0005
C(11)-Constant Term	-0.014644	0.008002	-1.829896	0.0675
Dlog(Newbuilding_Prices(-2))	0.172920	0.038672	4.471428	0.0000
Dlog(Secondhand_Prices(-1))	0.065535	0.014159	4.628347	0.0000
Log(SPOT(-3))	0.004199	0.001969	2.133062	0.0331
Dlog(Libor)	0.032811	0.013507	2.429241	0.0153
Dlog(Exchange_Rates)	-0.068700	0.029743	-2.309775	0.0210
Dlog(Steel_Prices)	0.151247	0.024803	6.097955	0.0000
Dlog(Scrap_Value(-1))	0.027308	0.013286	2.055440	0.0400

Spot Equation Diagnostic Tests			
Determinant residual covariance	7.02E-08	J-statistic	0.0504
R-squared	0.915359	Mean dependent var	3.8317
Adjusted R-squared	0.914479	S.D. dependent var	0.5730
S.E. of regression	0.167584	Sum squared resid	13.508
Durbin-Watson stat	1.991754		

The biggest impact derives from the time-charter rates (0,89), whose vessels of this category have long-term contracts (mainly two years and more). Consequently, spot rates are affected to a great extent from the current conditions in the time-charter market. One considerable contribution results from the dummy variable, which represents the closing of oil pipelines (0,18) as these vessels load directly from pipelines and tranship their cargo to smaller vessels.

Finally, second-hand prices (0,14) and newbuilding prices (0,17), which are included with two time lags are important for the formation of spot rates. Therefore, the positive impact of these two shipping markets is reduced in two time lags indicating that changes in these two markets would affect spot market after two months. The price of steel has significant positive impact (0,15). This points out that an increase in steel prices would affect newbuilding prices and consequently spot rates. Decision making and economic policy can rely on the second-hand and newbuilding prices, as they affect spot rates after two months. This time lag between spot market and second-hand and/or newbuilding market is a very useful tool in decision formation of participants in the shipping industry. The feedback effect, which represents SEMs with the correspondent dynamic multipliers of variables in Table 4, provides the necessary quantitative information to specify the future movement of spot prices.

4.1.2 Suezmax

The system with the smallest forecasting errors is that with two equations (Table 5). Endogenous variables are spot rates and newbuilding prices.

Log(SPOT)= 1,67 + 0,95*Log(Timecharter_Rate) -1,62*Dlog(Fleet_Dwt(-4))+ 0,03*Percentage_Gdp + [AR(1)=0,74] (5)

Dlog(Newbuilding_Prices)= 0,07*Dlog(Secondhand_Prices(-3)) +0,20*Dlog(Steel_Prices) + 0,03*Dlog(Libor) + 0,008*Dum_Regulation (6)

Table 5. SEM estimation and Diagnostic Tests (Suezmax)

Estimation Method: Generalized Method of Moments				
Included observations: 489 - Total system (unbalanced) observations 977				
Convergence achieved after: 1 weight matrix, 7 total coef iterations				
Variables	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C(1)-Constant Term	1.667462	0.122910	13.56649	0.0000
Log(Timecharter_Rate)	0.949355	0.045708	20.76995	0.0000
Dlog(Fleet_Dwt(-4))	-1.626526	0.683688	-2.379049	0.0176
Percentage_Gdp	0.032825	0.008633	3.802259	0.0002
AR(1)	0.743309	0.032270	23.03375	0.0000
Dlog(Secondhand_Prices(-3))	0.065836	0.028773	2.288143	0.0223
Dlog(Steel_Prices)	0.203503	0.025089	8.111311	0.0000
Dlog(Libor)	0.033846	0.015499	2.183725	0.0292
Dum_Regulation	0.008527	0.002085	4.090543	0.0000

Spot Equation Diagnostic Tests			
Determinant residual covariance	1.72E-05	J-statistic	0.0214
R-squared	0.940885	Mean dependent var	4.2654
Adjusted R-squared	0.940395	S.D. dependent var	0.5917
S.E. of regression	0.144459	Sum squared resid	10.079
Durbin-Watson stat	2.112598		

The Suezmax market is quite sensitive to new fleet capacity, as its coefficient represents the larger impact (-1,63) in spot rates. The fourth time lag between spot rates and fleet capacity provide the most valuable information for a decision maker.. The observation of fleet's capacity movement is the most appropriate quantitative measure of the spot rates' movement. This result is confirmed as during the period of economic crisis (2008:09-2011:02-end of the sample) the continuous increase of fleet capacity, has as a result the fierce decrease of spot rates. Time-charter rates also have a significant impact as the first-order autoregressive process AR(1) with a particular positive impact; this means that the first time lag of spot rates has a major impact in the current prices of spot rates. Steel prices affect spot rates significantly (0,20) as in the case of ULCC; with LIBOR, it is most obvious that spot rates are affected by economic cost variables. Because spot prices are dependent on previous macroeconomic variables, which are themselves dependent on the phase of economic cycle, the latter subsequently affecting the phase of the shipping cycle, this can best be explained by using an additional macroeconomic structural equation in SEM. The dummy variable of new regulation's introduction, although it is important statistically, has very small impact on spot rates.

4.1.3 Aframax

The system with the smallest forecasting errors during the static forecasting is that with the following endogenous variables: Spot rates, fleet capacity, second-hand and newbuilding prices.

Dlog(SPOT)= -0,08*Dlog(SPOT(-2))+ 0,91*Dlog(Timecharter)+ [AR(1)=-0,21] (7)

Dlog(Fleet_Dwt)= 0,001+ C(5)*Dlog(Fleet_Dwt(-1))+ 0,60*Dlog(SPOT) - 0,002*Dlog(Timecharter(-5))+0,014*Dlog(Newbuilding_Pr(-5))+[AR(1)=-0,36] (8)

Dlog(Secondhand_Prices)= -0,06+ 0,013*Log(SPOT(-1))+ 0,12*Dlog(Newbuilding_Pr.) + 0,21*Dlog(Secondhand_Pr.(-3))+ [AR(1)=0,30] (9)

Dlog(Newbuilding_Prices)= -0,02+ 0,18*Dlog(Newbuilding_Prices(-1))+ 0,04*Log(SPOT(-3))+ 0,08*Dlog(Secondhand_Pr.(-2)) + 0,18*Dlog(Steel_Pr.) (10)

Table 6. SEM estimation and Diagnostic Tests (Aframax)

Estimation Method: Generalized Method of Moments				
Included observations: 489 - Total system (unbalanced) observations 1951				
Convergence achieved after: 1 weight matrix, 13 total coef iterations				
Variables	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
Dlog(SPOT(-2))	-0.078277	0.023735	-3.298003	0.0010
Dlog(Timecharter_Rate)	0.907185	0.033949	26.72234	0.0000
AR(1)	-0.216417	0.039931	-5.419759	0.0000
C(4)-Constant Term	0.001204	0.000164	7.338095	0.0000
Dlog(Fleet_Dwt(-1))	0.600286	0.034566	17.36618	0.0000
Dlog(SPOT)	-0.002571	0.000818	-3.142757	0.0017
Dlog(Timecharter_Rate(-5))	-0.003743	0.001032	-3.625081	0.0003
Dlog(Newbuilding_Prices(-5))	0.014350	0.004866	2.949110	0.0032
AR(1)	-0.363978	0.040208	-9.052386	0.0000
C(10) -Constant Term	-0.059477	0.019663	-3.024855	0.0025
Log(SPOT(-1))	0.013494	0.004269	3.161078	0.0016
Dlog(Newbuilding_Prices)	0.119244	0.105836	1.126687	0.2600
Dlog(Secondhand_Prices(-3))	0.211776	0.121343	1.745260	0.0811
AR(1)	0.301907	0.042034	7.182452	0.0000
C(15) -Constant Term	-0.019932	0.008396	-2.373852	0.0177
Dlog(Newbuilding_Prices(-1))	0.183476	0.031458	5.832328	0.0000
Log(SPOT(-3))	0.004622	0.001811	2.552259	0.0108
Dlog(Secondhand_Prices(-2))	0.079047	0.023004	3.436267	0.0006
Dlog(Steel_Prices)	0.181446	0.023141	7.840843	0.0000
Spot Equation Diagnostic Tests				
Determinant residual covariance		6.92E-13	J-statistic	0.0672
R-squared		0.534862	Mean dependent var	-0.0020
Adjusted R-squared		0.532944	S.D. dependent var	0.2201
S.E. of regression		0.150457	Sum squared resid	10.979
Durbin-Watson stat		1.971187		

The system's estimations are statistically significant for all variables except this of newbuilding prices and that of second-hand prices with three time lags (Table 6). However, the newbuilding prices with five time lags and second-hand prices with two time lags are statistically significant. In this multiple equation system as in the systems of ULCC and Suezmax, time-charter rates and fleet capacity with time lag have the most intense impact on spot rates. In this market, SEM is very dynamic as most variables are estimated with time lags. The Aframax spot market is shaped in a very dynamic environment, which a decision maker must taking into account during the investment strategy or policy making. Also, steel prices, as an economic variable, affects positively spot rates with a similar parameter (0,18) as in ULCC is 0,15 and in Suezmax is 0,20.

4.1.4 Panamax

The best forecasting system is that with spot rates and second-hand prices as endogenous variables (Table 7. More specifically, equations are structured as follows:

Log(SPOT)= 0,49 + 0,90*Log(SPOT(-1))+1,00*Dlog(Timecharter_Rate)+
0,048*Dum_Regulation (11)

Dlog(Secondhand_Prices)= -0,03+ 0,35*Dlog(Secondhand_Prices(-1))+
0,007*Log(SPOT)-0,03*Dum_Economic_Crisis+ 0,045*Dlog(Scrap_Value) (12)

Table 7. SEM estimation and Diagnostic Tests (Panamax)

Estimation Method: Generalized Method of Moments				
Included observations: 492 - Total system (unbalanced) observations 984				
Linear estimation after one-step weighting matrix				
Variables	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C(1)-Constant Term	0.492463	0.130718	3.767359	0.0002
Log(SPOT(-1))	0.897662	0.027437	32.71735	0.0000
Dlog(Timecharter_Rate)	1.003402	0.428884	2.339564	0.0195
Dum_Regulation	0.047916	0.026495	1.808454	0.0708
C(5) -Constant Term	-0.027483	0.021893	-1.255327	0.2097
Dlog(Secondhand_Prices(-1))	0.345537	0.069408	4.978368	0.0000
Log(SPOT)	0.006782	0.004342	1.561760	0.1187
Dum_Economic_Crisis	-0.028554	0.028346	-1.007349	0.3140
Dlog(Scrap_Value)	0.045073	0.019326	2.332264	0.0199

Spot Equation Diagnostic Tests			
Determinant residual covariance	5.05E-05	J-statistic	0.005254
R-squared	0.864465	Mean dependent var	4.887969
Adjusted R-squared	0.863632	S.D. dependent var	0.483683
S.E. of regression	0.178615	Sum squared resid	15.56875
Durbin-Watson stat	1.955984		

These two equations have two basic characteristics. Firstly, this market is less affected by time lags, as only two predetermined variables (spot rates and second-hand variables) have time lags. Secondly, there is only one time lag, indicating that impacts are direct on the spot market and almost simultaneous.

Apart from time-charter rates, another important parameter is the effect of second-hand prices (0,35). Panamax market is one of the most active markets in asset play and exhibits interdependence between spot and second-hand markets. Also, spot prices with one time lag affect significantly current rates (0,90) indicating that spot rates are affected by endogenous variables and not so from exogenous economical variables. The presence of two dummy variables and especially that of economic crisis has the expected negative sign, which means that an economic crisis would affect the spot market negatively. New regulation would affect spot prices positively as history had showed in the case of Erika and Prestige packages, where spot prices had followed an increasing track.

4.1.5 Handysize

Handysize market is expressed with a system of two endogenous variables, spot rates and scrap prices.

Dlog(SPOT)= -0,19*Dlog(SPOT(-6))+ 0,73*Dlog(Timecharter_Rate) (13)

Dlog(Scrap_Value)= 0,08 -0,015*Log(SPOT(-5))+ 0,02*Percentage_Seaborne+ [AR(1)=0,07] (14)

Table 8. SEM estimation and Diagnostic Tests (Handysize)

Estimation Method: Generalized Method of Moments				
Included observations: 488 - Total system (unbalanced) observations 974				
Convergence achieved after: 1 weight matrix, 13 total coef. iterations				
Variables	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
Dlog(SPOT(-6))	-0.192073	0.046285	-4.149766	0.0000
Dlog(Timecharter_Rate)	0.734337	0.070562	10.40696	0.0000
C(3)-Constant Term	0.079293	0.044738	1.772356	0.0766
Log(SPOT(-5))	-0.015681	0.008838	-1.774317	0.0763
Percentage_Seaborne	0.019059	0.003815	4.996319	0.0000
AR(1)	0.066450	0.055764	1.191635	0.2337
Spot Equation Diagnostic Tests				
Determinant residual covariance		0.000214	J-statistic	0.01676
R-squared		0.282425	Mean dependent var	-0.00133
Adjusted R-squared		0.280945	S.D. dependent var	0.22781
S.E. of regression		0.193179	Sum squared resid	18.0992
Durbin-Watson stat		2.043458		

One characteristic of the model (Table 8) is that the examinant variable with six time lags presents high statistical significance. Current spot prices are affected by the past values in a period of six months. The main structural equation, which is solved together with spot equations, is the scrap prices equation. Indeed, Handysize market includes the highest number of ships (3.244 vessels at the end of the sample) and it is obvious that there is a large number of ships led for scrap in relation to other categories of vessels. Scrap prices also play an important role in the renewal of fleet as they can have a significant percentage of financing a new shipbuilding. Second-hand and newbuilding market seem that they don't have any important statistical significance in the formation of spot rates, as the Handysize market operates in a very different way in relation to other tanker markets. This conclusion is referred to the fact that costs in this market are much different (newbuilding cost, operating cost, voyage cost, etc.) in relation to other tanker markets, which make use of economies of scale. Operators in the Handysize market have as main priority to cover their costs as they cannot make use economies of scale. The interaction with the other shipping markets (second-hand and newbuilding) is very limited.

4.1.6 Historical and Ex-Post Forecasts - Tankers

The historical simulation of dynamic forecasting shows only the trend failing to capture the intense volatility of spot rates. On the contrary, static forecasts can predict with high accuracy the historical rates capturing the turning points of actual series. Static forecasts track actual series with high accuracy and are expected to give better out-of-sample forecasts. Historical simulations have smaller forecasting errors in relation to ex-post forecast, which means that the 12-month period of ex-post forecast is characterized by intense volatility.

4.2 Bulk carriers

4.2.1 Capesize

This multiple equation system is consisted of four endogenous variables, spot rates, fleet capacity and newbuilding and scrap prices (Table 9).

Dlog(Spot_Bulk)= 0,68*Dlog(Timecharter_Rate)+ 0,10*Dlog(Bunker_Prices)+
0,19*Dlog(Secondhand_Prices)+ [AR(1)=0,11] (15)

Dlog(Fleet_Dwt)= 0,01+ 0,13*Dlog(Fleet_Dwt(-1))- 0,002*Log(Spot_Bulk(-1)) (16)

Dlog(Newbuilding_Prices)= -0,01+ 0,15*Dlog(Newbuilding_Prices(-1))+
0,10*Dlog(Secondhand_Prices)+ 0,20*Dlog(Steel_Prices)+
0,006*Log(Timecharter_Rate(-1))+ 0,03*Dlog(Libor) (17)

Dlog(Scrap_Value)=0,01*Percentage_Seaborne+ 1,03*Dlog(Newbuilding_Pr.)+
0,11*Dlog(Scrap_Value(-6)) (18)

Table 9. SEM estimation and Diagnostic Tests (Capesize)

Estimation Method: Generalized Method of Moments				
Included observations: 488 - Total system (unbalanced) observations 1948				
Convergence achieved after: 1 weight matrix, 11 total coef iterations				
Variables	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
Dlog(Timecharter_Rate)	0.684412	0.035686	19.17893	0.0000
Dlog(Bunker_Prices)	0.102897	0.037268	2.761017	0.0058
Dlog(Secondhand_Prices)	0.194620	0.065172		0.0029
AR(1)	0.105853	0.044180		0.0167
C(5)-Constant Term	0.011131	0.002284	4.874161	0.0000
Dlog(Fleet_Dwt(-1))	0.131054	0.031395	4.174376	0.0000
Log(Spot_Bulk(-1))	-0.001924	0.000842	-2.285159	0.0224
C(8)-Constant Term	-0.012837	0.003468	-3.701927	0.0002
Dlog(Newbuilding_Prices(-1))	0.145993	0.042848	3.407228	0.0007
Dlog(Secondhand_Prices)	0.101000	0.012341	8.184050	0.0000
Dlog(Steel_Prices)	0.199160	0.028770	6.922438	0.0000
Log(Timecharter_Rate(-1))	0.005742	0.001581	3.631994	0.0003
Dlog(Libor)	0.028871	0.011535	2.502840	0.0124
Percentage_Seaborne	0.010155	0.003776	2.689308	0.0072
Dlog(Newbuilding_Prices)	1.026850	0.194254	5.286125	0.0000
Dlog(Scrap_Value(-6))	0.110903	0.027333	4.057418	0.0001

Spot Equation Diagnostic Tests			
Determinant residual covariance	1.85E-11	J-statistic	0.0749
R-squared	0.620151	Mean dependent var	0.0020
Adjusted R-squared	0.617791	S.D. dependent var	0.1342
S.E. of regression	0.083007	Sum squared resid	3.3279
Durbin-Watson stat	1.804556		

Most instrumental variables have one time lag and only scrap prices have more time lags. The most important shipping variables are time-charter rates, fleet capacity, newbuilding and scrap prices. There is also an economic variable, this of bunker prices which is not included in other vessel types. In addition, the percentage change of seaborne trade, the LIBOR and steel prices are the rest economic variables, which have statistical significance and affect spot rates in the Capesize market. This market is influenced by many economic variables, which means that it is necessary to built an additional macroeconomic SEM with structural equations of seaborne trade and LIBOR in order to specify spot rates more accurately.

4.2.2 Panamax Bulk

In the Panamax Bulk market, the multiple equation system has three equations, which include as endogenous variables spot rates, fleet capacity and scrap prices (Table 10).

Log(Spot_Bulk)= 1,72+ 0,66*Log(Timecharter_Rate)+
0,08*Dlog(Secondhand_Prices(-2))+ [AR(1)=0,96] (19)

Dlog(Fleet_Dwt)= 0,005+ 0,27*Dlog(Fleet_Dwt(-1))- 0,0008
*Log(Timecharter_Rate(-2)) (20)

Dlog(Scrap_Value)= 0,026*Dlog(Spot_Bulk(-4))+
1,14*Dlog(Newbuilding_Prices) + 0,02*Percentage_Seaborne (21)

Table 10. SEM estimation and Diagnostic Tests (Panamax Bulk)

Estimation Method: Generalized Method of Moments					
Included observations: 490 - Total system (unbalanced) observations 1467					
Convergence achieved after: 1 weight matrix, 10 total coef iterations					
Variables	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	
C(1)- Constant Term	1.716905	0.106528	16.11697	0.0000	
Log(Timecharter_Rate)	0.663453	0.033716	19.67760	0.0000	
Dlog(Secondhand_Prices(-2))	0.084120	0.046279	1.817668	0.0693	
AR(1)	0.957886	0.012510	76.57101	0.0000	
C(5)-Constant Term	0.005422	0.001722	3.148126	0.0017	
Dlog(Fleet_Dwt(-1))	0.274119	0.079902	3.430694	0.0006	
Log(Timecharter_Rate(-2))	-0.000786	0.000573	-1.371479	0.1704	
Dlog(Spot_Bulk(-4))	0.025769	0.034245	0.752484	0.4519	
Dlog(Newbuilding_Prices)	1.148363	0.399212	2.876572	0.0041	
Percentage_Seaborne	0.015642	0.007376	2.120466	0.0341	
Spot Equation Diagnostic Tests					
Determinant residual covariance		3.57E-09	J-statistic		0.0433
R-squared		0.915359	Mean dependent var		3.8317
Adjusted R-squared		0.914479	S.D. dependent var		0.5730
S.E. of regression		0.167584	Sum squared resid		13.508
Durbin-Watson stat		1.991754			

The system is very dynamic since most variables have time lags. Spot rates with four time lags present the longest period (memory), which affects the current series of spot rates. Newbuilding prices have the higher impact in spot rates (1,15). It is clear that in the Panamax Bulk market, there is a strong feedback between the spot and the newbuilding market. An increase in spot rates results in an increase in newbuilding price and vice versa. The effect is direct as there is no time lag between the two markets. A decision maker must take into account the high correlation, which exists in these two markets.

4.2.3 Handymax

SEMs in the Handymax market constitute of three equations, spot rates, fleet capacity and scrap value (Table 11).

Log(Spot_Bulk)= 0,06+ 0,98*Log(Spot_Bulk(-1))-2,23*Dlog(Fleet_Dwt(-4))+
[AR(1)=0,32] (22)

Dlog(Fleet_Dwt)= 0,27*Dlog(Fleet_Dwt(-1))-0,02*Dlog(Newbuilding_Pr.(-1))
+ 0,001*Log(Spot_Bulk(-1)) (23)

Dlog(Scrap_Value)= 0,007-1,63*Dlog(Fleet_Dwt(-3))+
0,21*Dlog(Newbuilding_Prices)+ 0,02*Percentage_Seaborne (24)

Table 11. SEM estimation and Diagnostic Tests (Handymax)

Estimation Method: Generalized Method of Moments					
Included observations: 489 - Total system (unbalanced) observations 1466					
Convergence achieved after: 1 weight matrix, 8 total coef iterations					
Variables	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	
C(1)-Constant Term	0.061860	0.025761	2.401301	0.0165	
Log(Spot_Bulk(-1))	0.984386	0.009146	107.6282	0.0000	
Dlog(Fleet_Dwt(-4))	-2.232146	0.966511	-2.309489	0.0211	
AR(1)	0.321429	0.046008	6.986356	0.0000	
Dlog(Fleet_Dwt(-1))	0.272160	0.043295	6.286251	0.0000	
Dlog(Newbuilding_Prices(-1))	-0.023880	0.007356	-3.246362	0.0012	
Log(Spot_Bulk(-1))	0.001007	9.86E-05	10.21866	0.0000	
C(8)-Constant Term	0.006922	0.003791	1.825924	0.0681	
Dlog(Fleet_Dwt(-3))	-1.633035	0.717544	-2.275868	0.0230	
Dlog(Newbuilding_Prices)	0.205264	0.155924	1.316433	0.1882	
Percentage_Seaborne	0.021225	0.003818	5.559263	0.0000	
Spot Equation Diagnostic Tests					
Determinant residual covariance		1.28E-09	J-statistic		0.0628
R-squared		0.915359	Mean dependent var		3.8317
Adjusted R-squared		0.914479	S.D. dependent var		0.5730
S.E. of regression		0.167584	Sum squared resid		13.508
Durbin-Watson stat		1.991754			

Fleet capacity has the main role in the estimation of the multiple equation system as expressed in three different time lags (one, three and four). Fleet capacity is the most valuable factor determining spot rates. More specifically, fleet capacity with four time lags has a negative impact with 2,23; with three time lags the multiplier decreases to 1,63. The one time lag affects positively only at 0,27. Another important variable is newbuilding prices expressed in both level and first time lags. The signs of parameters are the expected ones and especially current spot rates are affected by the past values of spot rates with one time lag positively.

4.3 Ex-Post and Ex-Ante Point forecasts

In this section, ex-post and ex-ante figures are presented for each vessel of tanker and dry bulk shipping markets. Ex-post point forecasts can be checked against the actual data and provide a means of evaluating a forecasting model and are characterized as in--sample forecasting. Ex-ante point forecast predicts the future values of spot prices beyond the original sample's period and is an out-of-sample forecast. Ex-ante forecasts can be used for decision making or policy making in either short-term or long-term time period.

4.3.1 Tankers

4.3.1.1 Ex-post forecasts

In all tankers markets, dynamic forecasts cannot track the intense volatility of actual prices for the period of the ex-post forecast (2010:03-2011:02). On the contrary, static forecasts outperform the dynamic and they can provide more accurate forecasts. More specifically, static forecasted series are quite close to the actual series following the general trend. From the figures 2, 3 and 4, it is obvious that the forecasted series reproduces the turning points of actual series (except for ULCC-VLCC) with one time lag. This result is confirmed quantitatively by the low values of forecasting errors based on RMSE and Theil as Table 12 shows. This means that the static ex-post forecasts can be used for ex-ante forecasting in the period 2011:03-2012:02.

4.3.1.2 Ex-ante forecasts

In the ULCC-VLCC market, ex-ante forecast shows an intense volatility for the entire period in fig. 2. Firstly, there is a decrease of spot rates, while for the last three months they follow an upward trend. In the Suezmax, ex-ante forecast has a smooth track with very low volatility. This is an indication that future spot rates would remain stable around their median (77, 81) with very few fluctuations.

Figure 2. Ex-post and Ex-ante forecasts ULCC-VLCC and Suezmax

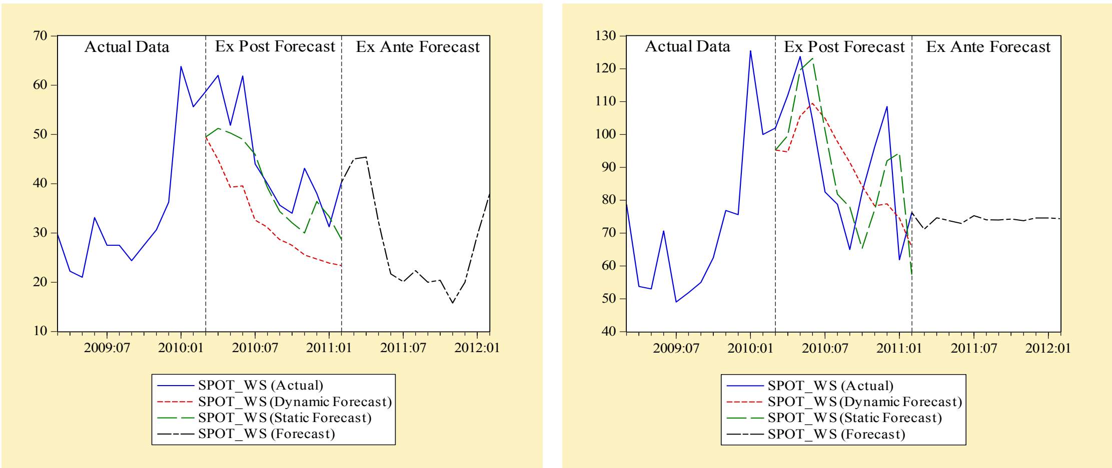
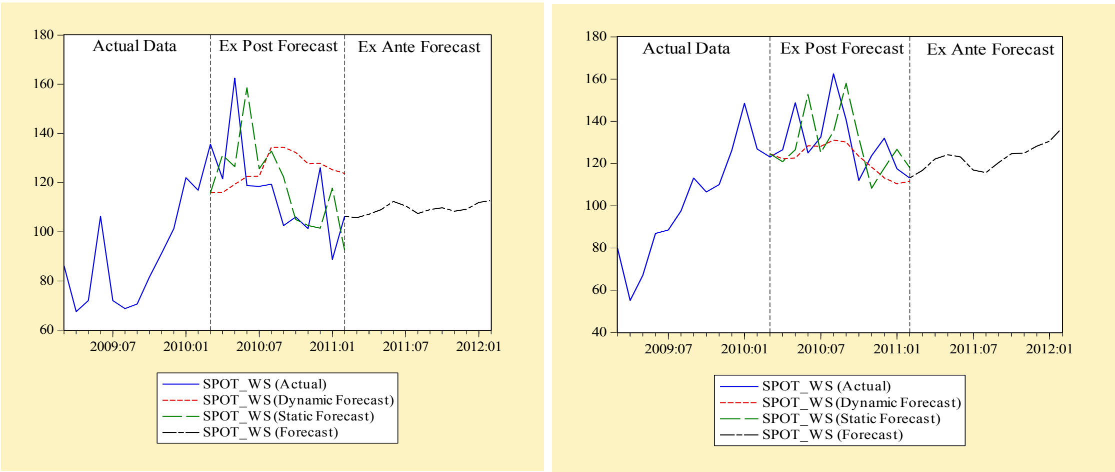


Fig. 3 shows that in the Aframax market, the ex-ante forecast follows a small increase in spot rates during the first four months, while for the remaining period forecasted series exhibit a more stable movement. In the Panamax sector, the ex-ante forecast follows an increasing trend with small volatility. A small decrease of spot rates is noticed at the middle of the forecasting period.

Figure 3. Ex-post and Ex-ante forecasts Aframax and Panamax



In the Handysize market, the ex-ante forecast is stable for the most part of the forecasting period (Fig. 4). There is only one small decrease in June 2011. The main result is that after a very intense volatility of spot prices in ex-post period the fluctuation of spot rates becomes very smooth.

Figure 4. Ex-post and Ex-ante forecasts Handysize

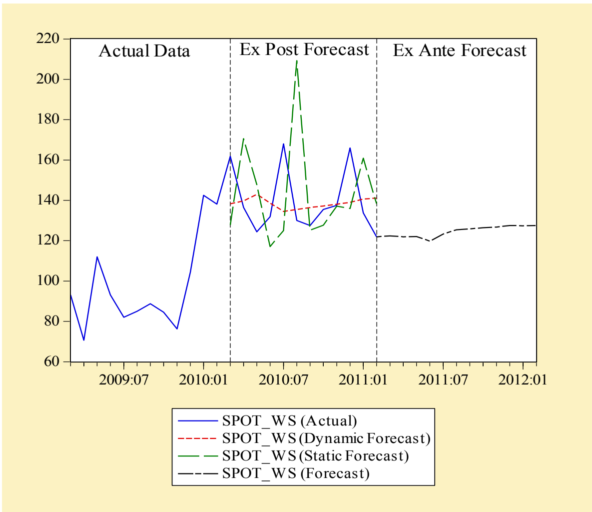


Table 12. Historical simulation and Ex-post forecast according to RMSE and Theil's Inequality Coefficient – Tankers

Historical Simulation 1970:01-2010:02				
	Dynamic Forecast		Static Forecast	
	RMSE	Theil Coef.	RMSE	Theil Coef.
ULCC-VLCC	14,185440	0,102434	9,898784	0,071070
Suezmax	21,289630	0,106578	14,817430	0,073257
Aframax	29,117850	0,117286	19,919660	0,078830
Panamax	55,811910	0,178586	28,675290	0,087686
Handysize	124,509800	0,392922	39,030880	0,093722
Ex post Forecast 2010:03-2011:02				
	Dynamic Forecast		Static Forecast	
	RMSE	Theil Coef.	RMSE	Theil Coef.
ULCC-VLCC	13,415980	0,167958	7,593052	0,087164
Suezmax	17,665980	0,095957	16,961570	0,091481
Aframax	23,412240	0,095973	21,648680	0,090489
Panamax	14,167120	0,056057	16,743750	0,064372
Handysize	16,683610	0,059811	33,162950	0,115910

4.3.2 Bulk Carriers

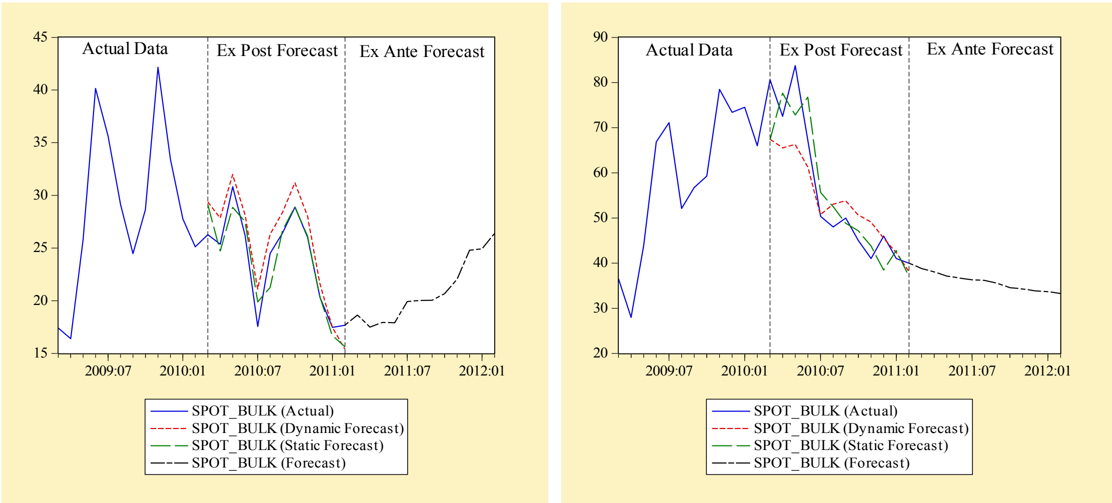
4.3.2.1 Ex-Post Forecasts

Historical simulations predict with great accuracy the actual series and the SEMs can be used for out-of-sample forecasts. Static forecasts outperform dynamic as they present much lower forecasting errors (Table 13). SEMs models have better applicability in the Capesize market (fig. 5) as they present in it the lowest forecasting errors. Also, the static forecast gives better forecasts in relation to the dynamic one as it can adapt to the turning points of actual series.

4.3.2.2 Ex-ante forecasts

In the Capesize market, the ex-ante forecast shows an increase of spot rates with a small volatility. After the intense fluctuations of ex-post period, the expectations are positive for shipowners about the future level of spot rates. In the Panamax Bulk market, the ex-ante forecast follows a very smooth decreasing trend (fig. 5). This forecast is influenced by the intense decrease of spot rates in previous months and it is obvious that expectations are negative regarding the spot market.

Figure 5. Ex-post and Ex-ante forecasts Capesize and Panamax Bulk



Finally, in the Handymax market (fig. 6), the forecast for the next 12 future observations has a very stable track. After a decrease of spot rates in ex-post forecasting period, SEMs present no important movement in future levels of spot rates.

Figure 6. Ex-post and Ex-ante forecasts Handymax

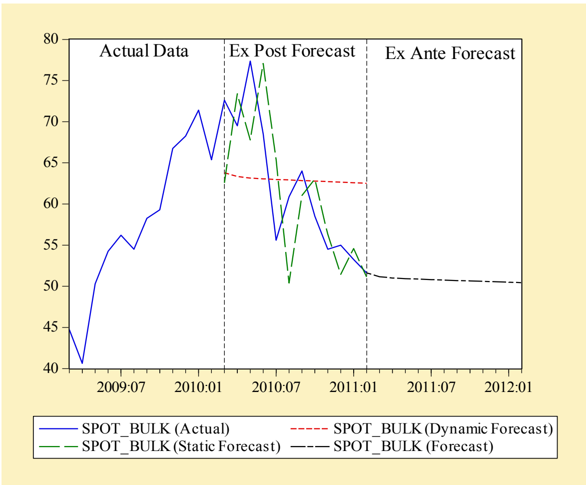


Table 13. Historical simulation and Ex-post forecast according to RMSE and Theil's Inequality Coefficient – Tankers

Historical Simulation 1970:01-2010:02				
	Dynamic Forecast		**Static Forecast**	
	RMSE	Theil Coef.	RMSE	Theil Coef.
Capesize	5,231173	0,151167	5,745650	0,049214
Panamax Bulk	9,108242	0,145626	3,518658	0,052722
Handymax	17,194200	0,318157	3,840125	0,060381
Ex post Forecast 2010:03-2011:02				
	Dynamic Forecast		**Static Forecast**	
	RMSE	Theil Coef.	RMSE	Theil Coef.
Capesize	2,178720	0,043196	1,710402	0,035182
Panamax Bulk	7,898919	0,059605	6,735321	0,058872
Handymax	7,945570	0,063435	6,675226	0,053802

5. Conclusions

During the estimation of SEMs and after the comparison of forecasts of 29 different systems, it is clear that the equations have the appropriate structure as the predetermined variables have high statistical significance. The joint solution of endogenous variables is characterized by accuracy and efficiency. In tanker market the second-hand and the newbuilding prices are the main endogenous variables where the mutual solution with spot rates gives the best forecasts.

More specifically, in the ULCC-VLCC and Aframax markets, shipping variables that are included in SEMs with spot rates are second-hand and newbuilding prices. This combination of endogenous variables presents the smallest forecasting errors. Respectively, second-hand prices are an important variable for Suezmax and newbuilding price for Panamax. In the Handysize market, the most important variable is scrap price. Among the three shipping markets (spot, second-hand, newbuilding) significant interdependencies are displayed, mainly for the first four vessel types. The variables of fleet capacity and time-charter rates are not important, as they do not have any endogeneity with spot rates.

In the bulk carrier market endogeneity of spot rates with fleet capacity and its time lags produce the best historical and ex-post forecasts, where the higher the number of lags the higher the negative impact on spot rates. Bulk carriers seem to be very sensitive to the existing fleet capacity and its variations affect spot market significantly. In addition, newbuilding and scrap prices affect the spot rates of bulk carriers negatively. Scrap prices are a decisive variable, because of their relation to the newbuilding market, since newbuilding prices are included in the scrap price equation as an exogenous variable. Then, newbuilding prices through a feedback effect have a significant impact on spot rates and vice versa. The joint solution of endogenous variables provides forecasts with higher precision and consistency in relation to the single equation models.

During the present economic crisis, there are intense downturns and upturns in spot rates as fig. 2- 6 present, which make even more difficult to have accurate long-term forecasts. Most SEMs include exogenous and predetermined variables with time lags, which mean that their past values affect the current spot rates in a dynamic environment. Forecasting is affected by these past values, which present great uncertainty because of the sharp increases and decreases of this period. However, SEMs generate ex-post forecasts, which are quite accurate. SEMs not only correctly forecast changing trends but also reproduce the turning points of spot rates. Long-term ex-ante forecasts of fig. 2- 6 show very clearly the future trend of spot rates, which can be used as additional criterion for decision makers.

Acknowledgements

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

Appendix

Table A1: Endogenous and exogenous variables for each vessel type in bulk shipping (Hausman Test)

	TANKERS				
Variables\ Vessels	**ULCC**	**Suezmax**	**Aframax**	**Panamax**	**Handysize**
Spot	Endogenous	Endogenous	Endogenous	Endogenous	Endogenous
Timecharter	Exogenous	Exogenous	Exogenous	Exogenous	Exogenous
Secondhand Pr.	Endogenous	Endogenous	Endogenous	Exogenous	Exogenous
Newbuilding Pr.	Endogenous	Endogenous	Exogenous	Endogenous	Endogenous
Scrap Value	Endogenous	Endogenous	Exogenous	Exogenous	Endogenous
Fleet capacity	Endogenous	Endogenous	Endogenous	Endogenous	Exogenous
% change of GDP	Exogenous	Exogenous	Exogenous	-------------	-------------
% change of Seaborne Trade	-------------	-------------	-------------	Exogenous	Exogenous

	BULK CARRIERS		
Variables\ Vessels	**Capesize**	**Panamax Bulk**	**Handymax**
Spot	Endogenous	Endogenous	Endogenous
Timecharter	Exogenous	Exogenous	Exogenous
Secondhand Pr.	Exogenous	Endogenous	Endogenous
Newbuilding Pr.	Endogenous	Endogenous	Endogenous
Scrap Value	Exogenous	Endogenous	Exogenous
Fleet capacity	Exogenous	Endogenous	Endogenous
% change of GDP	-------------	-------------	-------------
% change of Seaborne Trade	Exogenous	Exogenous	Exogenous

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