Full Length Research Paper

An analysis of the relationship between forward freight agreements and steel price index: An application of the vector ARMA model

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The bulk shipping market, as a global business, depends on the development of emerging industrial countries, the exploration of new mining areas, the policies of countries importing raw materials and the international economic situation. Due to market participants being able to decide independently the timing for entering or exiting the market, the type of vessel to invest in, the locations of shipping operations, and trading partners, this high level of independence and operation elasticity makes it difficult for market participants to control price volatility and trend. As such, market participants are reluctantly facing greater market uncertainty and volatility. Meanwhile, Forward Freight Agreements (FFAs) act as a very reliable hedging instrument, which enables market participants to hedge market risks by investing in FFAs. This research employs a time-series analysis, VARMA (Vector Autoregressive Moving-Average Model), as the methodology, using one year FFAs and the global steel price index as variables to analyze the coefficient between the two. This research is intended to provide market participants with a new direction for entering or exiting markets.

Key words: Forward freight agreements, steel price index, VARMA.

INTRODUCTION

The market prices of bulk shipping have the characteristics of high volatility and difficulty to control. If trading occurs only in spot markets at spot prices, bulk shipping prices will be volatile in the spot markets and participants will be unable to respond to the market situations. Therefore, market participants will eventually lose their competitiveness in the bulk shipping market and be immersed in the uncertain risks. During booming economic periods, the importance of monitoring market movements is not obvious. However, in a weak economy, the speed and quality of market information become rather essential. Therefore, Forward Freight Agreements (FFAs) are able to speed up market information movements and increase the quality of information. FFAs means that buyers and sellers reach a freight agreement which defines the specific sailing routes, prices, quantities and settlement dates, with the parties agreeing

to receive or pay the freight balance between the agreement prices and the Baltic dry index (BDI) at a future point of time. FFAs are a form of risk management for products including dry bulk specific routes, various vessels' forward freight agreements, specific crude oil routes and oil tankers' forward freight agreements (Su, 2008). In simple terms, the participants engage in FFAs mostly for at least one of the four motivations of derivative instruments: the risk hedging motivation, that is, to hedge the risk of spot assets or transportation costs; the speculation motivation, that is, to obtain a higher return by bearing risks using FFAs; the arbitrage motivation, that is, to discover the price imbalance between spot markets and derivative instrument markets; or the price discovery motivation, that is, to predict the market trends by using the derivative instrument market quoting system as the index (Chen, 2009).

Since 2003, the global economy has recovered gradually and the growth of China mainland GDP and Gross Industrial Output Value have increased perennially. Driven by the construction demand of the 2008 China

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Table 1. Forward freight agreements trading types.

Sailing route	Vessel type	Actual trading route	Vessel size	Contract unit	Price term	Settlement index
C4	Capesize	Richard Bay/Rotterdam	150,000 MT	1000 mt	USD/Ton	BDI
C7	Capesize	Bolivar/ Rotterdam	150,000 MT	1000 mt	USD/Ton	BDI
CS4TC	Capesize	Hybrid Route (C8, C9, C10, C11)	172,000 MT	Day	USD/Day	BDI
P2A	Panamax	Far East-Trip out	74,000 MT	Day	USD/Day	BDI
P3A	Panamax	Pacific Round Trip	74,000 MT	Day	USD/Day	BDI
PM4TC	Panamax	Hybrid Route (P1A, P2A, P3A, P4)	74,000 MT	Day	USD/Day	BDI
SM6TC	Handymax	Hybrid Route (S1A/B, S2, S3, S4/B)	54,000 MT	Day	USD/Day	BDI

Source: The International maritime exchange (IMAREX) (2010).

Olympic Games and the 2010 Shanghai World Expo, the demand for international shipping plunged. However, time charter and bulk shipping could not provide enough vessels to transport material punctually, and therefore international freight costs plunged rapidly. According to Steel Association research data released on the 3rd of November 2003, the freight of 40,000 bulks shipping from Brazil to Taiwan was U\$16/ton, but this figure jumped to U\$50/ton in December of 2003, increasing by 226%. Most of this freight increase was due to the demand for steel. As the essential material for construction, there will be a huge demand where the global economy is booming or a specific region is developing. Therefore, the demand for steel can be regarded as an essential index for measuring economic booms, and this demand movement is reflected by the price changes (BRS, 2003-2008). In recent years, increasing steel price fluctuations affected a number of related industries. From another point of view, freight shocks are increasing in severity. The purpose of this research is to analyze whether a one-way or two-way relationship exists between the global steel price index and the one-year forward freight with corresponding periods. The results of this correlation research are expected to be considered where participants of FFAs decide on entering or exiting markets.

REVIEW OF RELATED LITERATURE

For FFAs, as a Principal to Principal Contract, one party takes the view that the spot merchandise price on the agreed expiry date (settlement price) will be higher than the price agreed in the contract (contract price). However, another party holds the opposite opinion of the spot merchandise price being lower than the contract price on the agreed expiry date. Consequently both parties are willing to take this risk due to their different opinions of future market trends. When the contracts expire, one party will be the "winner" and the other will be the "loser", with the final settlement prices being based on the data defined by the sea freight agreement organizations (Baltic exchange). Freight derivative contracts only accept written hardcopy agreements and the difference between settlement prices and contract prices are paid in cash (Chen, 2009). Table 1 shows the detailed contents and types of FFAs.

Kavussanos and Nomikos (1999) find that future prices are able to predict whether bias exists in spot prices. This is because freight futures markets have lower trading volume compared to other markets, and thus future prices have a prediction ability of bias. Furthermore, for participants to hedge short term risks, it is not necessary to pay any risk premium when investing in spot markets. However, for long term contracts, investors have to compensate for hedging costs due to the prediction error of long term contract prices. Kavussanos and Alizadeh (2001) argue spot freight markets use tonnage as the pricing basis, and therefore smaller vessels have a higher average price per ton than bigger vessels. On the other hand, time charter markets use daily rates, such that bigger vessels have much higher prices than smaller vessels. However, if time charter vessels were transferred into tonnage rated spot markets, bigger vessels would still obtain comparatively lower average prices due to the economic scale of big vessels. Alizadeh and Nomikos (2003) believe that trading volume cannot affect prices dramatically and instead deliver the signals of market volatility. This effect indicates a greater trading volume generates lower market volatility. Therefore, if the futures market has low trading volume, the spot market prices can not be forecasted more precisely and the risks will increase as the error of long term forecasts increase. Adland et al. (2004) find for FFAs of specific vessel types, the forward freight agreements of four types of vessels: VLCC, Aframax, Capesize, Panamax, all have a risk premium. The different vessel type risk premium and time change risk premium all possess different characteristics. Kavussanos et al. (2004) suggest FFAs have the ability to stabilize the sailing route volatility when entering bulk shipping markets. However, it causes an unbalanced

impact to the two routes in the Pacific Ocean. Additionally, Kavussanos et al. (2004) also find the quality and speed of information movements have been improved after introducing FFAs. Batchelor et al. (2003) argued that it is necessary to select a suitable forecast model in order to achieve greater investing results when conducting speculating transactions. Kavussanos and Nomikos (2006) find that a single variable ARIMA model cannot present the correlation between variables, yet the application of VAR (Vector Autoregressive Model) can clearly distinguish the relationships between short term and long term variables. Thus, this research will apply a multivariable time series model to conduct the empirical analysis.

METHODOLOGY

In research analysis, the variables need to be considered are not limited to just uni-variables, but also the effect among multi-variables. In addition, it is necessary to build models for time series data, instead of a single series. When building models, it is impossible to understand which variables will affect another, or whether the variable is an exogenous or endogenous variable. Therefore, one must efficiently build a Vector Autoregressive moving-average model (VARMA model).

The main function of time-series data analysis method is to help researchers understand the correlations among indices in one system. In normal time-series analysis, most of the focus is on the measure and forecast of the relationship among indices. For the index, its movements are changed with time and environment. This research will discuss the relationships between FFAs and the global steel index, which considers an index movement to be a type of dynamic shocking. To obtain an effective forecast analysis, it is necessary to consider this characteristic. The VARMA model has the function to build the dynamic relationships between variables and increase the forecast accuracy. Selecting k vector with corresponding time periods (Yang, 2005):

$$\{Z_{1t}\}, \cdots, \{Z_{kt}\}, \ t = 0, \pm 1, \pm 2, \cdots \tag{1}$$

As demonstrated in matrix:

$$\underline{Z}_t = \left[Z_{1t,} \cdots, Z_{kt} \right]^{'} \tag{2}$$

Following this, the above data format can be called a time series with k vector and k degree matrix.

The random differences formula of normal ARMA(p, q) model with uni-variable Z_t (Tiao and Tsay,1983) is:

$$\phi_p \left(B \right) Z_t \ = \ C \ + \ \theta_q \left(B \right) a_t \tag{3}$$

B is the backward operator

$\left(\phi_1, \phi_2, \cdots, \phi_p \right)$ is called the autoregressive parameter

$\left(\theta_1, \theta_2, \cdots, \theta_p \right)$ is the average movement parameter

C is the constant

ARMA (p, q) model has the stable and invertible condition between

AR (p) and MA (q). If the result of $\phi_p \left(B \right) = 0$ falls outside of the unit circle, ARMA (p, q) remains stable. Ff the result of $\theta_q \left(B \right) = 0$ falls outside of the unit circle, ARMA has reversibility. Therefore, the vector ARMA model can be demonstrated as follows:

$$\underline{\phi}(B)\underline{Z}_t = \underline{C} + \underline{\theta}(B)\underline{\alpha}_t \tag{4}$$

Where $\underline{\phi}(B) = 1 - \phi_1 B - \cdots - \phi_p B^p$,

$\underline{\theta}(B) = 1 - \theta_1 B - \cdots - \theta_q B^q$

is the Matrix Polynomial of B, $\underline{\phi}$ and $\underline{\theta}$ are k×k matrix, $\underline{C}$ is k×1 fixed vector, $\underline{\alpha}_t$ is a series of independent normal distributed random moving vector, their average value is 0, covariance matrix is $\underline{\Sigma}$ and constant vector $\underline{C}$. Similarly, the constant C can be demonstrated as:

$$\underline{C} = (\underline{I} - \underline{\phi}_1 - \underline{\phi}_2 - \cdots \underline{\phi}_p)\underline{\mu} \tag{5}$$

The VARMA model can be modified as:

$$\underline{\phi}(B)\dot{\underline{Z}}_t = \underline{\theta}(B)\underline{\alpha}_t \tag{6}$$

Where $\dot{\underline{Z}}_t = \underline{Z}_t - \mu$.

Additionally, it is necessary to assume the results of the polynomial determinant $\left| \underline{\phi}(B) \right|$ and $\left| \underline{\theta}(B) \right|$ fall outside of the unit circle. When the results of $\left| \underline{\phi}(B) \right|$ fall outside of the unit circle, vector $\underline{Z}_t$ will be stable. When $\left| \underline{\theta}(B) \right|$ results fall outside of the unit circle, vector will be invertible.

Assume the final model is VARMA (1, 1), then $\underline{\phi}(B)\underline{Z}_t = \underline{C} + \underline{\theta}(B)\underline{a}_t$ can be simplified as:

$$\underline{I} - \underline{\phi}(B)\underline{Z}_t = (\underline{I} - \underline{\theta}B)\underline{a}_t \tag{7}$$

All of the elements of its matrix and vector can be written as:

$$\left\{ \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix} B \right\} \begin{bmatrix} Z_{1t} \\ Z_{2t} \end{bmatrix} = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - \begin{bmatrix} \theta_{11} & \theta_{12} \\ \theta_{21} & \theta_{22} \end{bmatrix} B \right\} \begin{bmatrix} a_{1t} \\ a_{2t} \end{bmatrix}$$
(8)

The parameter above ϕ_{ij} and θ_{ij} can be explained as the effect of the jth vector on the ith.

In order to measure the characteristics of the autoregressive model, Tiao and Box suggested the method of Partial Auto-regression (PAR) matrix in 1981. PAR matrix has the similar meaning in terms of the application of multivariate time series and the application of the univariate ARMA model.

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SIMPLIFIED SCAN TABLE (1% LEVEL):

Q:     0    1    2    3    4    5    6
------------------------------------------
0:     X    X    X    X    X    X    X
1:     X    0    X    X    X    0    0
2:     0    0    X    0    0    0    0
3:     X    0    0    0    0    0    0
4:     X    0    0    0    0    0    0
5:     X    0    0    0    0    0    0
6:     0    0    0    0    0    0    0
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Figure 1. The smallest canonical correlation analysis (SCAN) of raw data series.

The estimation of the lth in the PAR matrix can be calculated by fitting AR (l), and generally $\hat{\phi}_{ll}$ matrix is called $\hat{\underline{P}}(l)$. To obtain the PAR matrix, the format is required to fit a series of the autoregression model. Tiao and Box also mentioned that the format of the PAR matrix can be represented by symbols. When the standardised index is above 2, it can be shown as +, and when it is below 2, it is shown as -. If it is between the two values, • is used to represent this.

For building an AR model or MA model, the Cross correlation matrix (CCM) is rather useful for building a MA model, and the PAR is also useful for building the AR model. However, to establish a multivariate time series model, this research employs the simple method of measuring the mixed ARMA model suggested by Tiao and Box in 1984, which is the concept extension of the Cross correlation matrix. Thus, this method is named as the Extended Cross Correlation Matrix (ECCM). When considering 1 to 3 series, the application of ECCM is rather effective. Additionally, apart from the ECCM method, Tiao and Box developed the Smallest Canonical Correlation analysis (SCAN) to measure the ARMA model mixed with vector and time series. The SCAN method is not useful only for confirming the style of model, but also for measuring the correlation between series (Liu et al., 1992-1994).

EMPIRICAL ANALYSIS

This research employs the Panamax vessel's FFA index and global steel price index (CRU) between 2002 to 31st July 2009 as a variable series. After testing, it is found that the price index of FFAs for Panamax vessels belongs to the non-stationary series. In order to ensure series stability and reduce forecast error, it is necessary to take the logarithm of the raw data for analyzing. Due to long periods not representing such detailed change, and short periods not displaying the entire trend, this research applies the weekly data as the variable series. The total data collected included 396 cases. The first 376 cases (January 4th 2002 - March 13th 2009) are used as the in-sample simulated to forecast the future value. The 377th to 396th cases (March 20th 20009 to July 31st 2009) are used as the out-of-sample to conduct comparisons.

After measuring using SCAN (Figure 1), this research finds the likely orders of VARMA are VARMA (6, 0), VARMA (3, 1), VARMA (2, 3), VARMA (1, 5). Through comparing the simulated forecast value and actual index, and estimating the root mean square percentage error (RMSPE), we employed the Z_{1t} (FFA) series to predict Z_{2t} (CRU). The values are 8.6263%, 6.9833%, 6.3533%, 6.3741% respectively (Table 2), with the smaller RMSPE estimates representing a better prediction quality. Therefore, based on the estimation results, the RMSPE of VARMA (2, 3) is the smallest (6.3533%), and hence its forecast quality would be the best. Further, using Z_{2t} (CRU) to predict Z_{1t} (FFA), the RMSPE values are 6.2322%, 11.6605%, 9.5536%, 7.9824% (Table 3) respectively. The smallest value occurs in VARMA (6, 0), and thus VARMA (6, 0) is the best model when predicting Z_{1t} (FFA) through Z_{2t} (CRU) series.

After the above testing, it is discovered the fittest order for VARMA applying FFAs to forecast CRU is VARMA (2, 3). The order of AR indicates that FFAs are two periods ahead of CRU, and the change of current FFAs has a significant effect on CRU over the next two periods. However, the order of MA means its error adjustment factor has influence over three periods. When forecasting FFAs via CRU, the best fit order of VARMA is VARMA (6, 0), which indicates that the CRU is six periods ahead of FFAs, that is, the influence of CRU change will reflect on FFAs over 6 periods.

In addition, the RMSPE value of VARMA(6, 0) is 6.2322% when forecasting FFAs via CRU, although the RMSPE value of VARMA (2, 3) is 6.3533% when forecasting CRU via FFAs. From the RMSPE value prospective, CRU forecasting FFAs has better predicting quality than FFAs forecasting CRU.

CONCLUSION AND SUGGESTION

FFAs, as a risk management instrument, have received greater attention since 2004 with its functions exceeding the simple risk hedging purpose. During the great market volatility in 2004, FFAs provided participants with risk hedging function. However, when the market stabilized later, the FFAs market attracted more participants, and thus FFAs is not only useful a risk hedging instrument, but also as a tool for helping market participants gain profit. However, while FFAs are maturing, market participants have over speculated this derivative instrument. It is thus important to have a clear

Table 2. The root mean square percentage error results of FFA forecasting CRU model.

Model	VARMA(6, 0)	VARMA(3, 1)	VARMA(2, 3)	VARMA(1, 5)
RMSPE (%)	8.6263	6.9833	6.3533	6.3741

Source: this research.

Table 3. The root mean square percentage error results of CRU forecasting FFA model.

Model	VARMA(6, 0)	VARMA(3, 1)	VARMA(2, 3)	VARMA(1, 5)
RMSPE (%)	6.2322	11.6605	9.5536	7.9824

Source: this research.

market enter and exit strategy in order to prevent this risk hedging instrument from becoming detrimental.

The result of this research finds that FFAs and CRU have respective advanced influential periods, which means that the various forward/delay periods when one influences another. For FFA participants, the application of CRU to estimate future market trends is useful. However, for those who use steel prices as an operational factor, FFAs can be helpful in market forecasting. Even though the RMSPE value of VARMA (6, 0) is 6.2322% when forecasting FFAs via CRU, the value is still fairly small compared to 6.3533%, the RMSPE value of VARMA (2, 3) in forecasting CRU via FFAs. However, due to the forward periods being relatively longer, according to Kavussanos and Nomikos (1999), forecasts for longer periods will generate greater error. Therefore, for FFA market participants who wish to use CRU as the market monitoring index, it is necessary to pay attention to the interruption of unexpected events to forecasts during such periods, in order to make the most accurate operational decisions. Furthermore, as the time series adopted in this research are the one year Panamax vessel's FFA freight index, BPI has apparent seasonal effect according to Zhang et al. (2008), but BPI is also the sub-index of BDI – FFA's settlement index, and thus the seasonal effect should also be considered by market participants.

As per the empirical test of this research, the difference between the RMSPE values in the two forecasting methods is not significant. Therefore, the effect of the relationship that exists between FFAs and CRU suggests that the two series variables both have strong explanatory ability. As this research has not extensively analyzed the formulas with various orders, it is impossible to obtain clear conclusions about the coefficient relationship between the one-way and two-way relationship. This research is unable to demonstrate clearly whether correlation coefficients between two series variables are larger or smaller. In other words, dependent variables are unable to use numbers to demonstrate independent variables. This makes it difficult to measure the corre-lation coefficients and could improve in future research.

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