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# Full Length Research Paper

# Research on the relationship between forward freight agreements and the fuel oil index

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Bulk shipping is a globalised industry, and market prices are entirely dependent on the world's economic climate. The industries contractual arrangements are also rather flexible making it difficult for market participants to understand the trends and fluctuations of market prices and forcing market participants to face greater uncertainty and volatility. Oil and Forward Freight Agreements (FFAs) act as suitable hedging instruments in bulk shipping markets, allowing market participants to hedge their risks in spot markets. This research predominantly applies the vector autoregressive moving-average model (VARMA) and uses variables from one year FFAs and the global oil index to analyse the relationships between the two instruments. This research believes the VARMA (1,3) is the most suitable model, because it demonstrates the existence of a stage one lag effect between Capesize FFAs and the global oil index. This model also has three error correction factors. By using VARMA (1,3) formulas, it is possible to discover the mutual effects of the relationship between the two hedge components. The research result aims to provide market participants with guidance for entering and exiting bulk shipping markets.

**Key words:** Forward freight agreement (FFAs), oil index, vector autoregressive moving-average model (VARMA).

## INTRODUCTION

Pricing in bulk shipping markets is highly uncertain because of the degree of flexibility involved. The bulk shipping market is a globally competitive market, and as a result, its prices are significantly affected by changes in the world economic climate (Kavussanos, 1996). For operators and managers in the shipping industry, understanding the relationship between the variables that influence pricing in shipping markets has the potential to

Abbreviations: FFAs, Forward Freight Agreements; VARMA, vector autoregressive moving-average model; BDI, Baltic Dry Index; BRS, Barry Rogliano Salles; BCI, Baltic Capesize Index; BFA, Baltic Forward Assessments; BIFFEX, Baltic International Freight Futures Exchange; BFI, Baltic Freight Index; OTC, over the counter; ARIMA, autoregressive integrated moving average; DF, Dickey-Fuller; PAR, Partial Autoregression; SCAN, smallest canonical correlation analysis; BWI, Bunker world Index; BBP, Bunkerworld Benchmark Prices; RMSPE, root mean square percentage error.

reduce risk and increase profit. An ability to predict future trends successfully will be extremely helpful when making decisions on asset allocations and risk management (Cullinane, 1995). Bulk shipping operators confirm that Forward Freight Agreements (FFAs) are able to increase the rate of movement of market information and the quality of market information in the dynamic bulk shipping market (Chou and Huang, 2010).

FFAs are a type of freight contract agreed between a seller and buyer. The contract terms define specific shipping routes, prices, quantity, and payment periods. Both contracting parties agree to collect or pay the difference between the FFA contracted price and the price based on the Baltic Dry Index (BDI) at a specified future date. Essentially, FFAs are a risk hedging instrument. FFAs include different specific shipping routes and have forward freight terms for various vessels, for example the contract specifications of the Panamax FFA index and the Capesize FFA index, which are different. Kavussanos et al., (2004) believed that FFAs have functioned as stabilizers

of the volatility in the price of shipping routes since they became part of the bulk shipping market. Compared to forward freight, fuel oil prices are also a strong interactive factor on forward freight obligations. This is because fuel is a fixed cost for all bulk shipping vessels and the fuel oil price is a vital factor for the industry. Therefore, fuel oil costs become one of the key items measured by both time charter and voyage charter parties in bulk shipping arrangements. Looking at FFA's from the perspective of risk hedging, there are four motivational factors that apply to the majority of participants in FFAs: the risk hedging motive, speculation motive, arbitrage motive and price discovery motive (Chen, 2009). In terms of motives, fuel oil prices and FFAs apply these four motives simultaneously; signing long term contracts for spot assets or transportation costs is a goal of hedging risks. The arbitrage motive, which hedges the spread between spot markets and derivative commodity markets, and the price discovery motive are reference standards which are used to forecast market trends using derivative commodity market pricing systems. These motives demonstrate that fuel oil price movement and forward freight price movement require consideration of similar issues.

According to the reports of BRS (2009) and UNCTAD (2008), the global economy recovered gradually from 2003 due to strong construction demand from the China Olympics and the 2010 Shanghai Expo. China's increasing demand for raw material has strengthened international shipping markets (Chou and Lin, 2010). However, liner shipping and bulk shipping were unable to provide sufficient vessels for raw material transportation and this caused a substantial jump in international freight costs. The BRS (2008) reports show that, at the end of June 2006, Capesize vessels' shipping capacity was extremely tight as Australian and Brazilian mineral exporters were unwilling to accept vessels older than 25 years and, additionally, BHP (a mining company) occupied one mineral ore port for an entire month, severely restricting port access. This supply shortage caused the price of the Baltic Capesize Index (BCI) to increase sharply. Meanwhile, the BDI showed a rapid price increase, also reaching a historical high in 2008. At that time, both time and voyage charters were showing an upward trend. Considering these rental increases, professional managers in the bulk shipping industry started to adopt financial derivative instruments as risk hedging tools. In traditional bulk shipping, the steel price index and the BDI are the predominant reference standards for risk hedging (Chou and Lin, 2010). The BDI is used to discover current and historic movements in bulk shipping rates. The steel price index is the main index for bulk raw material and, if required, can be used as the key index to measure economic climate. Of the two indices steel price index. six-stages ahead of the BDI, is the better indicator of pricing trends in the bulk shipping markets (Chou and Lin, 2010). However, FFAs are rather different in taking a twostage lead ahead of the steel price index (Chou and

Huang, 2010), and therefore, it is clear that FFAs are better risk hedging instruments compared to the other two indices.

The Global Financial Crisis in 2008-2009 spread through the entire world, and without exception, the bulk shipping market was also affected. Due to increasing uncertainty in the external environment, the risk fluctuations in bulk shipping markets have increased dramatically. These uncertainties have also influenced the volatility of bulk shipping freight, resulting in a price increase. Fuel oil is a substantial fixed cost for the bulk shipping industry. In order to comprehensively understand the industry's risks and the usefulness of FFA's as a hedging instrument, the BWI, being the fuel oil index, needs to be considered. This paper, therefore, aims to discover useful information for researchers and investors in the bulk shipping industry through analysis of the BWI and FFAs. This research adopts the global fuel oil index and one-year FFA specifications to analyse whether there is a unidirectional or bidirectional relationship between the two factors. It is expected to explain the relationship of these indicators and provide analysis for market participants to consider when making decisions to enter into this market.

## LITERATURE REVIEW

The Baltic Forward Assessments (BFA) is an estimated average price of bids and offers for the dry and wet freight market based on submissions from brokers registered in London at 17.30 GMT (London). The Baltic International Freight Futures Exchange (BIFFEX) introduced freight futures trading in 1985. The futures contract is a basket of freight rates designed to reflect the daily price movement in fright rate of eleven dry bulk spot voyage and time charter routes (Kavussanos and Nomikos, 1999). This contract was written on Baltic Freight Index (BFI) and was also the world's first futures contract based on a service rather than a physical asset. However, since 1992 the competing over the counter (OTC) market for FFA's has given ship owners and charters the ability to hedge their physical contracts in the spot freight market (The Baltic Exchange, 2011). Between June 2000 and 2002, the BDI remained fairly stable; the index movement was not significant at approximately 2,000 points (Clarkson Research Studies, 2008). According to Ekawan et al. (2006), steel production regions have been reallocated since 1950, shifting from Europe and America to Asia, with the average growth rate being 5% between 1998 and 2007. In terms of iron ore, South America and Australia became the main export countries, and Asia turned into the main import region, in particular China, which is an important iron ore import country in this area (Chou and Lin, 2010). Based on the statistical data from BRS (2008), between 2000 and 2002, the freight from Newcastle, Australia to Rotterdam,

**Table 1.** Freight of shipping routes for Capesize and Panamax 2000 to 2002.

Vessel	Shipping route	Cargo	Freight (USD/MT)
Capesize	Newcastle Australia to Rotterdam Netherlands	Coal	~7- 17
Capesize	Tubarao Brazil to Far East area	Iron ore	~3- 9
Panamax	US GUIF to Japan	Cereal	~15-25
Panamax	Richards Bay South Africa to Le Havre France	Coal	~5-13

Source: BRS (2009).

Table 2. Trading method of FFAs.

Route Type	Vessel	Actual route	Capacity (MT)	Trading unit (Each order)	Price term	Transaction Reference Index
C4	Capesize	Richard Bay/Rotterdam	150,000	1,000 mt	USD/Ton	BDI
C7	Capesize	Bliver/ Rotterdam	150,000	1,000 mt	USD/Ton	BDI
CS4TC	Capesize	Combined route (C8, C9, C10, C11)	172,000	days	USD/Day	BDI

Source: The International Maritime Exchange AS (2010).

Netherlands for a 140,000 MT Capesize coal vessel (The International Maritime Exchange AS, 2010), shown in Table 1, was about U\$7-17 per MT. For a 145,000 MT Capesize iron ore vessel, the freight was U\$3-9 per MT, from Tubarao Brazil to Far East Asia (BRS, 2009). Since 2003, across all shipping industries, the bulk freight shipping market has experienced the most dramatic volatility. At the end of June 2006, Australian and Brazilian mineral exporters refused to accept vessels older than 25 years. Furthermore, BHP (a mining company) maintained its mineral ore port for one month. These circumstances restricted the shipping capacity of Capesize (BRS, 2009). In 2007, the BDI reached 11,000, its historical high. In the same year, once it was obvious that iron ore prices were to increase, panic buying occurred in the March 2007 quarter. Factors such as fast global economic growth, raw material price increases, inflation and strong shipping demand combined with the vital 2007 iron ore price negotiations forced the FFA price to reach its historical high of 142,500 in October 2007. The profit taking of FFA market participants generated selling pressure and the FFA index started decreasing rapidly in October 2008. In July 2010, the FFA stands at 25,250. FFA is, at present, a financial derivative product used by bulk shipping companies and mining companies. The FFA market is maturing along with the transparency of information, and is attracting more investors into the market. Alizadeh-M and Nomikos (2003) believed iron ore Capesize vessels have a capacity utilisation rate of 70 and 45% for coal. Since the principle transportation equipment for iron ore and coal is Capesize vessels, this paper adopts the Capesize FFA index as the key subject index.

From 2002, the shipping industry started to recover. Along with the growth from China and other emerging countries, the demand for coal and steel increased

rapidly. Astier (2001) indicated that developing a nation's economy has created a huge demand for raw materials, especially on imported iron ore and coal items. This is evident through the demand during 2002-2008. At the moment, China is the major importer in Asia and iron ore exports mainly come from Australia and South America. Coal export, however, is principally from Australia and Indonesia. The report by Clarkson (2008) also mentioned that, at present, the global coal mining industry is actually influenced by economic demand from Asian countries. Capesize vessels are mainly used as iron ore and coal shipping equipment. According to Table 2, the current three shipping routes all have a vessel capacity of approximately 150,000 MT, priced in US dollar. Apart from CS4TC route, which is charged by days, all other routes' charges are based on 1.000MT. The BCI index began to rise and reached its historical high in 2008. According to Table 2, C4 and C7 currently account for approximately 10% of all FFA trades (Freight Investor Services, 2011). Traded routes on the BCI are the Richards Bay/Rotterdam C4, Bolivar/Rotterdam C7, and the Average of the 4 Time Charter Routes.

Through comparison of spot freight and forward freight, Kavussanos and Nomikos (1999) believed forward freight prices are a relatively better forecast tool. Therefore, this article applies one-year forward freight agreements as the key index. In terms of risks, short-term investors pay lower additional costs. However, for the longer term, forecast error will increase and, accordingly, the risk will increase (Alizadeh-M and Nomikos, 2003). Due to the difference in the size of vessels, the risk premium of vessel size and time premium have various characteristics (Adland et al., 2004). For example, vessels for iron ore and coal shipping are much bigger compared to cereal vessels. Therefore, their economies of scale are much

different (Alizadeh-M and Nomikos, 2003). As a result, this research applies the FFA of Capesize vessels as the principle index. Since the global fuel oil index and one-year forward freight agreements are the indicator indices, the autoregressive integrated moving average (ARIMA) model is unable to discover the relationship between variables (Kavussanos and Visvikis, 2006). Hence, this research applies VARMA model to determine the leading or delay relationship between the two indices to conduct experimental analysis of variables.

## **METHODOLOGY**

For macro economists, there are four research focuses. These are: (1) describing macro time series change; (2) forecasting macro time series; (3) characterizing the casual structure of macro time series; (4) analysis of macro economy (Stock and Watson, 2001). The time series analysis method has all the four functions above and, Hansen and West (2002) take it as one of the three major methods of time series analysis in the last 25 years. Many papers have used the time series models presented in this model as well as forecasting financial time series such as the forward pricing, spot price volatility and time charter freight rates and so on (Kavussanos et al., 1999; Kavussanos et al., 2004; Kavussanos and Alizadeh, 2001). During research and analysis, it may be necessary to consider that variables are not only univariable but can also be the result of multivariable and causation relationships between variables. However, the majority of previous literature on shipping related research focuses on the measurement and forecasting of historical data through a single index. Therefore, for FFA and the fuel oil index, its movement trend will change along with the events and economic climate. This paper aims to discuss the relationship between FFA and the global fuel oil index. In other words, the fluctuations of the index are a type of dynamic vibration and, in order to conduct an effective forecast analysis, it must be examined in greater detail. VARMA model has the function of constructing the dynamic relationship between variables and increasing forecast accuracy (Hamilton, 1994). The vector ARMA model can be demonstrated as follows:

$$\phi(B)\underline{Z}_{t} = \underline{C} + \underline{\theta}(B)\underline{a}_{t}$$

Where 
$$\underline{\phi}(B) = \underline{I} - \underline{\phi}_1 B - \dots - \underline{\phi}_p B^p$$
,  $\underline{\theta}(B) = I - \underline{\theta}_1 B - \dots - \underline{\theta}_q B^q$ 

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

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

The VARMA model can be modified as:

$$\underline{\phi}(B)\underline{\underline{Z}}_t = \underline{\theta}(B)\underline{a}_t$$

$$\underline{\underline{Z}}_t = \underline{\underline{Z}}_t - \underline{\mu}$$
 where

The FFA and BWI in the VARMA model are variables which must be conducted for each unit root test to confirm the number of columns and BWI/FFA series that can be processed through the unit root test in identifying a unit root test. These are the only two series for this Causality test, otherwise the variable can only test the cointegration between the phenomenon (co-integration), the phenomenon being when a non-stationary regression relationship between variables may produce false causality. The concept of cointegration was developed by Engle and Granger (1987). Cointegration implies that, although two series (BWI and FFA-CAPE) are non-stationary, or integrated, such that first differences are required to become stationary, a linear combination of these series can be stationary (Hamilton, 1994). Since an unweighted difference between two series FFA and BWI, that is, FFA-BWI, can also be described as the vector product CI (1, 1). (FFA-CAPE, BWI), one can refer to these differences as CI (1, 1) linear combinations. In this study, we restrict our attention to the augmented Dickey-Fuller (DF) test (Dickey and Fuller, 1979), since it is widely used (Mills, 1990). The null hypothesis for the DF test is that the FFA-CAPE/BWI series is non-stationary with a unit root. Assume our

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:

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

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

$$\left\{ \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix} B \right\} \begin{bmatrix} FFA - CAPE_t \\ BWI_t \end{bmatrix} = \left\{ \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - \begin{bmatrix} \theta_{11} & \theta_{12} \\ \theta_{21} & \theta_{22} \end{bmatrix} B \right\} \begin{bmatrix} a_{1t} \\ a_{2t} \end{bmatrix}$$

The parameter above  $\phi_{ij}$  and  $\theta_{ij}$  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 autoregression (PAR) matrix in 1981. PAR matrix has a similar meaning in terms of the application of multivariate time series and the application of the univariate ARMA model.

The estimation of the lth in the PAR matrix can be calculated by

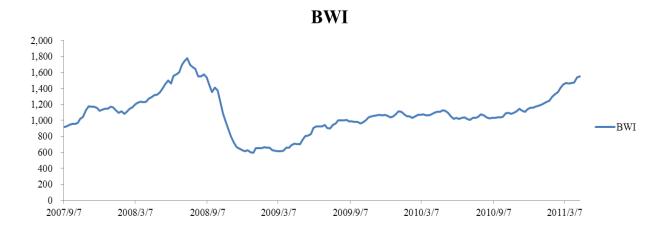
fitting AR(I), and generally 
$$\hat{\phi}_{II}$$
 matrix is called  $\hat{\underline{P}}(I)$ .

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 (Liu et al., 2004).

For building an AR model or MA model, 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., 2005).

## **EXPERIMENTAL ANALYSES**

The Bunkerworld Index (BWI) is a weighted daily index made up of 20 key bunkering ports (Bunkerworld, 2011). To take a representative geographical spread, the ports were selected by size with reference to their geographical importance. The BWI is transparent and independently



### FFA-CAPE 160,000 140,000 120,000 100,000 80,000 FFA-CAPE 60,000 40,000 20,000 2007/9/7 2008/3/7 2008/9/7 2009/3/7 2009/9/7 2010/3/7 2010/9/7 2011/3/7

Figure 1. BWI and FFA-CAPE series.

calculated based on the accurate and highly regarded Bunkerworld Benchmark Prices (BBP). The BBP is set for each port every day at a certain time and is included in the Index. The BWI, as a whole, is set daily at 18:00 GMT (Bunkerworld, 2011). The sample period covers five years and extends from September 2007 to April 2011, yielding 189 weekly observations. Our BWI data was downloaded from Bounkerword. In Figure 1, before September 2008, BWI had a minimum value of 914 and maximum value of 1,775, holding an average level of 1,286. Due to the impact from the Global Financial Crisis, between September 2008 and May 2009, the BWI reached its lowest level and averaged just 729, a historical low for the BWI. Currently, the average value is 1,013 with a standard deviation of 79.

FFAs offer ship owners, charterers and traders a means of protecting themselves against the inherent volatility of freight rates. The Capesize FFA-CAPE is arguably the segment within the family of freight derivative products that provides the best indicator of market direction. In terms of the routes traded, port flexibility and product carried, this vessel size is the most limited. Iron ore and both steam and coking coal are the drivers for the underlying physical market (Freight Investor Services,

2011). Increasingly, Capesize FFAs offer considerable liquidity in the short and medium terms and also progressively offer strategies for longer term trading/hedging opportunities, often up to 2-3 years forward (Freight Investor Services, 2011). Currently the most liquid trading is found on the average of the four time Charter routes using a variety of days and guarters. Data for the period September 2007 to April 2011 are from Simpson Spencer and Young Limited (SSY Limited), yielding 189 weekly observations. Prior to August 2008 (Figure 1), the minimum of FFA-CAPE was 13,000 and its maximum value was 10,250. Its average value remained historically high. Due to the impact of the Global Financial Crisis, FFA-CAPE was in a dramatic decline from August 2008 to January 2009. The current average FFA-CAPE stands at 26,825.

Nelson and Plosser (1982) showed that, general economic indicators generally have a unit root. Enders (2004) suggested drawing a graph of the process unit test. This paper applies the FFA-CAPE over September 7th 2007 to April 15th 2011 and BWI as the variable series. There are 189 weekly data sets. The null hypothesis for the DF test is that FFA/BWI series is non-stationary with a unit root.

**Table 3.** Augmented-Dickey-Fuller test.

5.

6:

0

0

Variable		Original series				Difference original series			
FFA		-2.424			-5.358*				
BWI		-1.887			-4.440*				
	Q:	0	1	2	3	4	5	6	
	0:	?	?	?	?	?	?	?	
	1:	?	?	?	0	0	0	0	
	2:	0	0	0	0	0	0	0	
	3:	?	0	0	0	0	0	0	
	4:	0	0	0	0	0	0	0	

Figure 2. Smallest canonical co-relation analysis.

0

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Table 4. Estimation result of model's root mean square percentage error using VARMA model to forecast BWI.

Model	VARMA(1,3)	VARMA(2,1)	VARMA(3,1)	VARMA(4,0)
RMSPE	1.732%	1.748%	1.748%	1.791%

Source: This research.

In this paper, we analyzed the data after taking natural logarithms. This overcomes comparability problems in the data, since the series originate from quite different sections of the FFA/BWI. Taking logarithms also stabilizes the variances of the series, and reduces the impact of heteroscedasticity. In Table 3, we show that, all series are non-stationary at the 10% level. This means that the null hypothesis is not rejected at the 10% level since the original number as non-stationary series, such that first differences are required to obtain stationary. The results from Table 3 show that all series are stationary at the 1% level. We can describe this as the vector product two variables have CI (1, 1). These a long-run equilibrium relationship between economic phenomena.

In order to maintain the stability of series and reduce forecasting errors, this research calculates the logarithm of raw data to simplify future analysis. It has also been considered that a greater interval will not show detailed changes while shorter intervals will not demonstrate the entire trend. Therefore, this research adopts weekly data as the variable series. There are a total of 189 weekly data sets, 10 of which will be used to measure the suitability of the model and judge the quality of the recreated model.

After studying the figures of SCAN (Figure 2) in this

research, the possible optional models of VARMA model include: VARMA(1,3), VARMA(2,1), VARMA(2,1) and VARMA(4,0). Comparing the simulated forecast value and the actual index, and then evaluating this through the root mean square percentage error (RMSPE) using the VARMA model to estimate the FFA-CAPE series, the values are 1.732, 1.748, 1.748 and 1.791% (Table 4) respectively. The smaller RMSPE estimated value is the more reliable forecast. Therefore, in terms of evaluation, VARMA(1,3) has the smallest RMSPE value having 1.732% as its result. Hence, its forecasting quality is the best. Furthermore, using the VARMA model to forecast BWI series, its RMSPE values are 4.048, 4.411, 4.222 and 4.286% (Table 5) respectively. The smallest value appears in VARMA(1,3), hence, VARMA(1,3) would be the best model to forecast BWI via the BWI series.

Through verification of the above, it can be concluded that VARMA(1,3) is the best model to forecast BWI/FFA-CAPE relativities. By adding all RMSPE values together, it is possible to find that VARMA(1, 3) has the smallest RMSPE value. As a result, VARMA (1, 3) is the best fit model in the research of FFA-CAPE and BWI. This model demonstrates that there is a one-weekly delay effect between the FFA-CAPE and BWI, and there are three To understand the level of effect that FFA-CAPE and BWI

Table 5. Estimation result of model's root mean square percentage error using VARMA model to forecast FFA.

Model	<b>VARMA(1,3)</b>	<b>VARMA(2,1)</b>	<b>VARMA(3,1)</b>	<b>VARMA(4,0)</b>
RMSPE	4.048%	4.411%	4.222%	4.286%

Source: This research.

error correcting factors in existence. We are able to

present all coefficients in the matrix thus:

$$\begin{bmatrix} FFA - CAPE_t \\ BWI_t \end{bmatrix} = \begin{bmatrix} 0.191 \\ (0.103) \\ 0.053 \\ (0.086) \end{bmatrix} + \begin{bmatrix} 0.981 \\ (0.010) \\ 0.993 \\ \vdots \\ (0.012) \end{bmatrix} \begin{bmatrix} FFA - CAPE_{t-1} \\ BWI_{t-1} \end{bmatrix} + \begin{bmatrix} a_{FFA-CAPEt} \\ a_{BWh} \end{bmatrix} - \begin{bmatrix} 0.226 & -1.161 \\ (0.072) & (0.284) \\ -0.062 & -0.367 \\ (0.015) & (0.070) \end{bmatrix} \begin{bmatrix} a_{FFA-CAPEt-1} \\ a_{BWh-1} \end{bmatrix} - \begin{bmatrix} \vdots \\ a_{BWh-1} \end{bmatrix} -$$

have on each other, the matrix can be displayed as follows:

$$FFA-CAPE_t = 0.191+0.981 FFA-CAPE_{t-1} + a_{FFA-CAPE_{t-1}} - 0.226 a_{FFA-CAPE_{t-1}} + 1.161 a_{BWI_{t-1}} + 0.244 a_{BWI_{t-3}}$$

$$^{BWI}_{t} = 0.053 + 0.993 \ ^{BWI}_{t-1} + ^{a_{BWIt}} + 0.062^{a_{FFA} - CAPEt-1} + 0.367^{a_{BWIt-1}} + 0.244^{a_{BWIt-3}}$$

From the two formulas above, it can be deciphered that FFA-CAPE is under a one-weekly impact from itself and BWI. For FFA-CAPE itself, it receives a positive effect from its first stage. Additionally, it receives a positive effect from BWI's MA stage. As per BWI, it also receives an impact from itself and the one stages of FFA-CAPE's MA stage. It can be found that the first stage MA impact on FFA-CAPE is positive, and through the FFA-CAPE of experience and a weight also consider the price of the next. Empirical analysis of the two variables, BWI to FFA-CAPE, indicates the following relationships:

Firstly, FFA- CAPE series of BWI series prediction model prediction model VARMA optimal order of VARMA(1,3), while the VARMA(1,3) for the FFA-CAPE series of BWI series do predict the best model, so the two series on the best mode of the order of each other are all VARMA(1,3). Secondly, the impact of the previous week can be found for the FFA-CAPE/BWI. Thirdly, the ADF-test results showed that FFA-CAPE and BWI has a co-integration of these two variables in the phenomenon, FFA-CAPE on the long-run equilibrium between BWI phenomena.

## **CONCLUSIONS AND SUGGESTIONS**

Fuel oil price itself has the characteristic of risk management

(Kavussanos and Nomikos, 1999). BWI, therefore, actually has a great impact on fuel oil prices. However, FFA has become another type of risk management instrument applied since 2004 by managers in the shipping industry (Chou and Huang, 2010). The function provided by either FFA or BWI is not purely that of hedging risk, but also stabilizing shipping freight (Kavussanos et al., 2004). During 2004, in a period of increasing market fluctuations, shipping managers hedged risks by initially using FFA and BWI. Whilst increasing market transparency attracts more participants, current FFA and BWI have abandoned pure risk hedging functions. Along with more professional managers starting to operate FFA and BWI in order to develop a better position to hedge risks or speculate. FFA markets at present have continued the speculative atmosphere. Guided by the correlation between FFA and BWI provided by this research, professional shipping managers will have a clear strategy on entering and leaving this market and, as a result, will be able to prevent increased risks due to speculative markets.

This paper finds that, FFA-CAPE and BWI have leading effective stages respectively, which also means one variable has different leading or delay stages to itself and the other variable. For managers who need to consider steel prices as a factor, FFA-CAPE can be used to assist in judging the market. Kavussanos and Nomikos (1999) suggested that longer term forecasting will cause greater errors. Therefore, for FFA market participants, if applying BWI as the observation index, it is necessary to acknowledge the effect of emergency on forecasting in order to make the best decisions for operating purposes. Additionally, this paper applies the one-year Capesize vessel FFA. BCI, however, is a division index of BDI, which is the transaction index of FFA. Therefore, market participants should also consider seasonal effects.

Through the evidence of this paper, the best model for this research is VARMA(1,3). This model indicates there is one-stage behind effect between FFA and BWI, with a three error correction factor. According to the formulas, it can be found that a bidirectional relationship exists between the two variables.

The results presented in this article indicate that an economically meaningful structure exists in a set of BWI and that there are stable long-run relationships between FFA-CAPE.

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## **REFERENCES**

- Adland R, Jia H, Koekebakker S (2004). The pricing of forward ship value agreements and the unbiasedness of implied forward prices in the second hand market for ship. Maritime Econ. Logist., 6(2): 109-121.
- Alizadeh MAH, Nomikos NK (2003). The price-volume relationship in the sale and purchase market for dry bulk vessels. Maritime Policy Manage., 30(4): 321-337.
- Astier JE (2001). The evolution of the world iron ore market. Mineral and Energy Raw Mater. Rep., 16(4): 23-30.
- Barry Roglian Salles (2009). The dry bulk market in 2008. Shipping and Shipbuilding Market. pp. 24-31.
- Bunker World (2011). Bunkerword Index. April 30, 2011. Retrieved: http://www.bunkerworld.com/prices/index/bwi
- Chen YS (2009). The theory and practice of bulk shipping management. Taiwan: Liwen PLC.
- Chou MT, Lin SC (2010). An analysis of the relationships between baltic dry index and steel price index - an application of the vector AR model. J. Chinese Instit. Transport., 22(2): 211-232.
- Chou MT, Huang BC (2010). An analysis of the relationship between forward freight agreements and steel price index an application of the vector ARMA model. Afr. J. Bus. Manage., 4(6): 1149-1154.
- Clarkson Research Studies (2008). Shipping Intelligence Weekly. London: Claskson PLC.
- Cullinane K (1995). A portfolio analysis of market investments in dry bulk shipping. Transport. Res., 19(3): 181-200.
- Dickey DA, Fuller WA (1979). Distribution of estimators for autoregressive time series with a unit root. J. Am. Stat. Society, 74(366): 427-43 1.
- Ekawan R, Duchene M, Goetz D (2006). The evolution of hard coal trade in the pacific market. Energy Pol., 34(14): 1853-1866.
- Ender W (2004). Applied econometrics time series. Enders, W. (2004), Applied econometric time series. 2nd Edition. New York: John Willey and Sons Inc. p. 357.

- Engle RF, Granger CWJ (1987). Cointegration and error correction Representation, estimation and testing. Econometrica, 55(2): 251-276.
- Freight Investor Services (2011). Capesize FFA. Retrieved April 30, 2011, from http://www.freightinvestorservices.com/freight/ffas
- Hamilton JD (1994). Time Series Analysis, Princeton University Press: 544-570.
- Hansen BE, West KD (2002). Generalized method of moments and macroeconomics. J. Bus. Econ. Stat., 20(4): 460-469.
- Kavussanos MG (1996). Price risk modeling of different size vessels in the tanker industry using autoregressive conditional heteroscedastic (ARCH) models. Logistics Transport Rev., 32(2): 161-176.
- Kavussanos MG, Nikos K, Nomikos NK (1999). The forward pricing function of the shipping freight futures market. J. Futures Mark., 19(8): 353-376.
- Kavussanos MG, Alizadeh AH (2001). Seasonality patterns in dry bulk shipping spot and time charter freight rates. Transport. Res., 37(6): 443-467
- Kavussanos MG, Visvikis ID, Batchelor RA (2004). Over—the-counter forward contracts and spot price volatility in shipping. Transport. Res., 40(3): 273-296.
- Kavussanos MG, Visvikis ID (2006). Shipping freight derivatives: a survey of recent evidence. Maritime Pol. Manage., 33(3): 233-255.
- Liu LM, Hudak GB, Box GEP, Muller ME, Tiao GC (2004). Forecasting and time series analysis using the SCA statistical system. Sci. Comput. Assoc. Corp., 1(5): 44-5\_46.
- Liu LM, Box GEP, Tiao GC (2005). Forecasting and time series analysis using the SCA statistical system. Sci. Comput. Assoc. Corp., 2: 4.4-4.11
- Mills TC (1990). Time Series Techniques for Economists (reprint 1992). Cambridge University Press. Cambridge. United Kingdom.
- Nelson CR, Plosser CI (1982). Trends and random walks in macroeconmic time series: some evidence and implications. J. Monetary Econ., 10(2):139-162
- Stock JH, Watson MW (2001). Vector autoregressions. J. Econ., Perspect., 15(4): 101-115.
- The Baltic Exchange (2011). FFA. Retrieved April 30, 2011, from http://www.balticexchange.com/
- The UNCTAD Secretariat (2008). Review of Maritime Transport 2008. United Nations.
- The International Maritime Exchange (2010). Dry Bulk Freight Futures. April 30, 2010. Retrieved: http://www.exchange.imarex.com