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Correlations and Volatility Spillovers between the Carbon Trading Price and Bunker Index for the Maritime Industry[1]

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Abstract: This research intends to investigate the relationship between carbon trading price and the bunker fuel index, with inputs from reviewing current greenhouse gas (GHG) mitigation management and financial measures, for the purpose of evaluating the cost implications of carbon price on the maritime industry. The Dynamic Condition Correlation Model (DCC Model) is applied for evaluating the variations of the carbon trading price and the bunker fuel index, in the light of an analysis of the proportion of fuel hedging to be used and the hedging performance. With the results of hedging performance, the cost implications of GHG mitigation management measures are investigated.

Keywords: Carbon trading price; Bunker fuel index; Constant Condition Correlation Model; Dynamic Condition Correlation Model

JEL Classifications: C43, E32, D46, E60

1. Research Background

The issues related to carbon footprint, carbon neutrality and carbon trading have become one of the most discussed topics over the past years. With the reduction of greenhouse gases (GHGs) being the main issue on the agenda of the International Maritime Organization (IMO), the maritime industry has been gradually adjusting its business model and evaluating the impacts of GHG emissions (IMO, 2009). The IMO officially proposed examining GHG emission issues in 1997. The Marine Environment Protection Committee (MEPC) agreed to establish GHG related policies in 1998 and these have been in force since February 2005 (IMO, 2011, 2012). The United Nations Framework Convention on Climate Change (UNFCCC) meetings have failed to include the shipping industry in the Kyoto Protocol, as carbon emissions are set on a national level and the high seas are excluded (UNFCCC, 2008). In 2013, the MEPC established the Energy Efficiency Design Index (EEDI) and the Ship Energy Efficiency Management Plan (SEEMP) as the energy

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standards for new ships. All new ships above 400 tonnes have to meet the new EEDI requirements, the energy index has to be reduced by 10%, with a further reduction of 10% between 2020 and 2024, to achieve the 30% reduction target after 2024. Existing ships have to meet relevant energy requirements as well. This could be considered the first regulatory energy standard for all ships in the world and the first specialized regulation for international maritime GHG emission reduction. In addition, the Energy Efficiency Operational Index (EEOI) was established in January 2013. All new ships have to be built according to the EEOI, in order to achieve the target by 2050 (IMO, 2014).

A few countries and regions in the world have implemented various forms of emission trading scheme as a means of mitigating the impacts of carbon emissions. These schemes, such as those in the United Kingdom, Japan, New Zealand and China, generally involve different domestic industries. Australia imposed a carbon tax in July 2012 as a step towards implementing a carbon trading scheme in the near future. Given the similar international nature of both the aviation and maritime industries, it might be expected that carbon price might affect the operating costs of the shipping industry if and when market-based measures (MBMs) are implemented. The carbon price varies according to the degree of application of emission mitigation measures and the maritime market dynamics (Lutz *et al*, 2013). With the enforcement of the EEDI and EEOI by IMO, the improved fuel efficiency of new ships might in turn affect the carbon market.

The European Union Emission Trading Scheme (EU ETS) has been one of the main platforms of global carbon trading and related issues, as the European Union has relatively more stringent policies and measures on GHG emissions than the rest of the world. With the inclusion of aviation in the EU ETS, and with their involvement in environmental issues and sustainable fuels worldwide, the maritime industry will have to face incorporating their carbon price into operating costs at some point in the future.

Although, carbon taxes/charges or costs have not been considered one of the cost items for the shipping industry, the industry cannot be excluded from carbon-related measures for long. With fuel cost being 30-40% of the total operating costs of the industry in general, understanding carbon emissions from the combustion of fuel during transport phases, and the correlation between carbon price and the bunker fuel index, are seen as an interesting issues to be investigated: what are the correlations and volatility spillovers between carbon trading price and bunker fuel index? This is the main issue to be resolved in the project.

2. Literature Review

With respect to financial management, the modern enterprise emphasizes the source, applications and management of capital (Brealey *et al.*, 2003), and the maritime industry is no exception. As fuel cost is one of the most important operating costs for the maritime industry, and given that the cost of GHG emissions might be applied to the maritime carriers through MBMs, understanding the relationship between carbon price and bunker fuel index in order to implement hedging policies has become a necessary task to be conducted. The Constant Condition Correlation Model (CCC Model) and Dynamic Condition Correlation Model (DCC Model) have already been applied extensively in the finance area (Bekiros and Diks, 2008; Büttner and Hayo, 2011; Chou, 2012; Morana and Beltratti, 2008; Engle, 2002; Hassan and Malik, 2007; Kenourgios et al., 2011; Manolis et al., 2011; Noureldin, 2012; Sadorsky, 2012; Syriopoulos and Roumpis, 2009; Tu et al., 2008), however, there is only limited application in the maritime industry. With the relaxation and liberalisation of the maritime industry, there is a need to understand the dynamic relationship between different markets. So far, there is little discussion on the evaluation of GHG

emissions and fuel, and even on the hedging research between carbon price and fuel price.

Correlation has been an area of importance. With the development of econometric models and computer acceleration, related risk assessment has improved enormously as well (Francq and Zakoïan, 2010). Following the presentation of the Autoregressive Conditional Heteroskedasticity (ARCH) model by Engle in 1982 (Engle, 1982) , there is a change from the traditional assumption of homogeneous variance to varying variances though time. This has led to Bollerslev (1986) to expand the ARCH model into the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, which enables more flexibility for estimated parameters and models. As the GARCH model progresses, traditional financial articles have focused on analysis using the CCC model. But then, with the development of DCC model, most literature has found that worked better than the CCC model, but this is not an absolute, as it varies with different data series analyzed (Francq and Zakoïan, 2010).

Most risk evaluation has applied both CCC and DCC models at the same time for the setting of hedging performance models (Noureldin, 2012; Sadorsky, 2012). Compared to the CCC model, the DCC model has two distinct advantages: (a) it enables an easier estimation of dynamic correlation, resolving the calculation complexity of conditional heteroskedastic matrix; (2) for capital which might result in volatility with time, the use of a dynamic relationship has solved the research limitation on constant coefficients (Francq and Zakoïan, 2010; Tu et al., 2008; Noureldin, 2012; Sadorsky, 2012).

3. Methodology

After Engle proposed the ARCH model in 1982, Bollerslev (1986) extended the model into the GARCH model, which was used extensively in finance related literature. (Bekiros and Diks, 2008; Büttner and Hayo, 2011; Chou, 2012; Morana and Beltratti, 2008; Engle, 2002; Hassan and Malik, 2007; Kenourgios et al., 2011; Manolis et al., 2011; Noureldin, 2012; Sadorsky, 2012; Syriopoulos and Roumpis, 2009; Tu et al., 2008) The main econometric model applied in this research is the DCC model within the scope of the GARCH model.

Assume a multivariate GARCH process (Francq and Zakoïan, 2010), all past data on ϵ_{kt}, concerning all the variables $\epsilon_{l,t-i}$, is summarized in the variable $h_{kk,t}$, with $Eh_{kk,t} = E\epsilon_{kt}^2$. Then, letting $\tilde{\eta}_{kt}$=$h_{kk,t}^{-1/2}\epsilon_{kt}$, define for all k a sequence of independent identically distributed (i.i.d.) variables with zero mean and unit variance. The variables $\tilde{\eta}_{kt}$ are generally correlated, so let $R = \mathrm{Var}(\tilde{\eta}_t) = (\rho_{kl})$, where $\tilde{\eta}_t = (\tilde{\eta}_{1t}, \dots\dots, \tilde{\eta}_{mt})'$.

The conditional variance of $\epsilon_t = diag(h_{11,t}^{1/2}, \dots, h_{mm,t}^{1/2})\,\tilde{\eta}_t$ is then written as

$$H_t = diag\left(h_{11,t}^{1/2}, \dots, h_{mm,t}^{1/2}\right)\mathrm{R}\; diag\left(h_{11,t}^{1/2}, \dots, h_{mm,t}^{1/2}\right) \qquad (1)$$

By construction, the conditional correlations between the components of ϵ_t are time-invariant:

$$\frac{h_{kl,t}}{h_{kk,t}^{1/2}h_{ll,t}^{1/2}} = \frac{E(\epsilon_{kt}\epsilon_{lt}|\epsilon_u, u<t)}{\{E(\epsilon_{kt}^2|\epsilon_u, u<t)|E(\epsilon_{lt}^2|\epsilon_u, u<t)\}^{1/2}} = \rho_{kl}.$$

To complete the specification, the dynamics of the conditional variances $h_{kk,t}$ has to be defined. The simplest constant conditional correlations (CCC) model relies on the following univariate GARCH specifications:

$$h_{kk,t}=\omega_k + \Sigma_{i=1}^{q} a_{k,i}\epsilon_{k,t-i}^2 + \Sigma_{j=1}^{p} b_{k,j}h_{kk,t-j}, \qquad \mathrm{k} = 1,\dots, \mathrm{m} \qquad (2)$$

where ω_k>0, $a_{k,i} \geq 0$, $b_{k,j} \geq 0$, -1$\leq \rho_{kl} \leq$1, ρ_{kl} = 1, R is symmetric and positive semi-definite. Observe that the conditional variances are specified as in the diagonal model. The conditional covariance is clearly non-linear in the squares and cross products of the returns (Francq and Zakoïan, 2010).

To extend the specification (2) by allowing $h_{kk,t}$ to depend not only on its own past, but also on the past of all the variables $\epsilon_{l,t}$ (Francq and Zakoïan, 2010), let

$$\underline{h}_t = \begin{pmatrix} h_{11,t} \\ \vdots \\ h_{mm,t} \end{pmatrix}, \; D_t = \begin{pmatrix} \sqrt{h_{11,t}} & 0 & \cdots & 0 \\ 0 & \ddots & & \\ \vdots & & & \\ 0 & & \cdots & \sqrt{h_{mm,t}} \end{pmatrix}, \; \underline{\epsilon}_t = \begin{pmatrix} \epsilon_{1t}^2 \\ \vdots \\ \epsilon_{mt}^2 \end{pmatrix}.$$

Definition [CCC-GARCH(*p*, *q*) process] Let (η_t) be a sequence of i.i.d. variables with distribution η. A process (ϵ_t) is called CCC-GARCH(p, q) if it satisfies

$$\begin{cases} \epsilon_t = H_t^{1/2}\eta_t \\ H_t = D_t R D_t \\ \underline{h}_t = \underline{\omega} + \sum_{i=1}^{q} A_i \underline{\epsilon}_{t-i} + \sum_{j=1}^{p} B_j \underline{h}_{t-j} \end{cases} \quad (3)$$

where R is a correlation matrix, $\underline{\omega}$ is an $m \times 1$ vector with positive coefficients; both A_i and B_j are $m \times m$ matrices with non-negative coefficients.

Letting $\epsilon_t = D_t\tilde{\eta}_t$, where $\tilde{\eta}_t = R^{1/2}\eta_t$ is a centered vector with covariance matrix R. The components of ϵ_t thus have the usual expression, $\epsilon_{kt} = h_{kk,t}^{1/2}\tilde{\eta}_{kt}$, but the conditional variance $h_{kk,t}$ depends on the past of all the modules of ϵ_t. (Francq and Zakoïan, 2010).

The Engle (2002) dynamic conditional correlation model is estimated in two steps. In the first step, the GARCH parameters are estimated. In the second step, the correlations are estimated. Therefore, the constant matrix R is replaced by a matrix R_t which is measurable with respect to the past variables $\{\epsilon_u, u < t\}$. It seems sensible to choose diagonal matrices A_i and B_i in equation (3), corresponding to univariate GARCH models for each components as in equation (2). Different DCC models are obtained depending on the specification of R_t (Francq and Zakoïan, 2010). The formulation is:

$$R_t = \theta_1 R + \theta_2 \psi_{t-1} + \theta_3 R_{t-1} \quad (4)$$

where the θ_i are positive weights summing to 1, R is a constant correlation matrix, and ψ_{t-1} is the empirical correlation matrix of $\epsilon_{t-1}, \ldots, \epsilon_{t-M}$. The matrix R_t is thus a correlation matrix. Equation (4) is reminiscent of the GARCH(1,1) specification, $\theta_1 R$ playing the role of the parameter ω, θ_2 that of α, and θ_3 that of β (Francq and Zakoïan, 2010). The dynamics of R_t are given by setting

$$R_t = (\text{diag } Q_t)^{-1/2} Q_t (\text{diag } Q_t)^{-1/2}$$

where diag Q_t is the diagonal matrix constructed with the diagonal elements of Q_t, and Q_t is a sequence if covariance matrices which is measurable with respect to σ $(\epsilon_u, u < t)$. A normal parameterization is

$$Q_t = \theta_1 Q + \theta_2 \epsilon_{t-1}\epsilon'_{t-1} + \theta_3 Q_{t-1} \quad (5)$$

where Q is a covariance matrix. Again, the formulation recalls the GARCH(1,1) model. Though different, both specifications (4) and (5) allow us to test the hypothesis of constant conditional

covariance matrix by considering the restriction $\theta_2 = \theta_3 = 0$ Note that the same θ_2 and θ_3 coefficients are found in the different conditional correlations, which thus have very similar dynamics. The matrices R and Q are often estimated/replaced by the empirical correlation and covariance matrices. In this article, a DCC model of the form (4) or (5) thus introduces only two more parameters than the CCC formulation (Francq and Zakoïan, 2010). In this paper, we estimate the univariate volatility using the GARCH(1,1) model, and standardized residuals are used to estimate the correlation parameters.

4. Empirical Analysis

This paper used weekly logarithm data, expressed as "return margin" in the following analysis. The return margin means transforming data[2] on the carbon trading price, given in EU Allowance (EUA) units of one tonne of CO_2, and the Bunker world index (BWI) of bunker fuel into the natural logarithm form $r_{i,t} = \ln(P_{i,t}/P_{i,t-1})$, of which $r_{i,t}$ denotes the weekly return margin of the tth week, $P_{i,t}$ is the EUA of the *i*th week EUA and the BWI of the *t*th week. Before conducting the DCC analysis, this research firstly analyzed the EAU and BWI data for the purpose of the later GARCH model analysis.

There are in total 198 weekly datasets for the period between 30 July 2007 and 15 June 2013. The average number, standard error, coefficient of skewness and coefficient of kurtosis are used for the basic statistical analysis. The basic statistics characteristics in table 1 shows that the return margin is negative for EAU, and positive for BWI. On the other hand, EAU has a higher standard error, meaning a higher range in return margin and potentially higher risk as well. As regards the coefficient of skewness, the coefficients for both EAU and BWI are lower than 0, meaning that these two datasets skew to left. A coefficient of kurtosis greater than 3 indicates a leptokurtic distribution. The statistics results show that the EAU and BWI are both non-normal distributions, therefore the general assumption of normal distribution is rejected. Figures 1 and 2 show that both EUA and BWI exhibit a gathering effect.

Before conducting the time series analysis, this research used the ADF single root test to verify whether the data comply with the static status assumption. The unit root test of the EAU and BWI return margins in Table 1 confirm that the EAU and BWI are both in the form of static time series data and do not have unit root characteristics.

Table 1 The basic statistics characteristics and unit root test of the EAU and BWI return margins

	Basic Statistics Characteristics					**Unit Root Test**		
	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	None	Intercept	Trend and Intercept
EAU	-0.810	6.158	-0.872	4.937	55.785***	-9.501***	-9.635***	-9.746***
BWI	0.259	3.270	-0.992	6.181	115.773***	-4.268***	-4.275***	-4.284***

Note: *** indicates the statistical significance level of $p < 0.01$

[2] Both data sets obtained from ICE Europe.

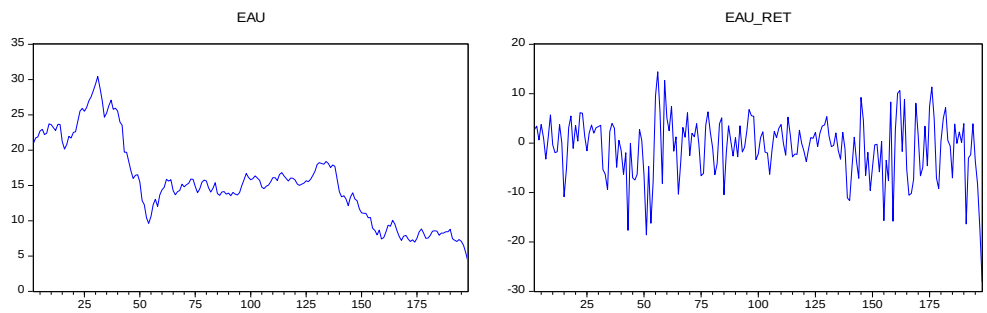

Figure 1 EAU and EAU return margins

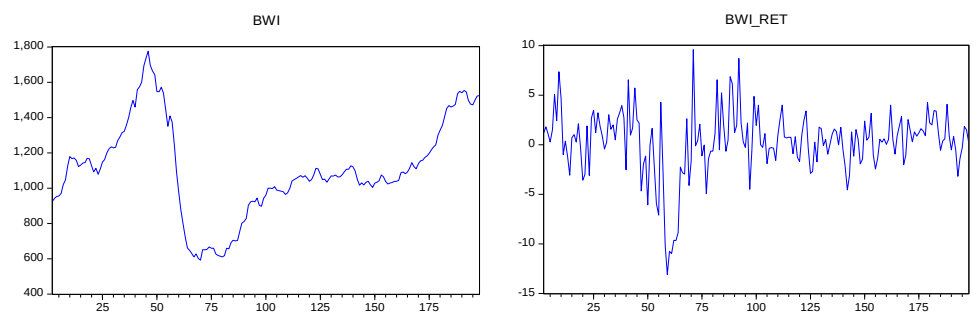

Figure 2 BWI and BWI return margins

The DCC model is used for the estimation of the second stage (Francq and Zakoïan, 2010). The first stage estimates the GARCH(1,1) model of EAU and BWI. The second stage uses the residual value for estimating the DCC parameters. The GARCH(1,1) model for both data series are as follows,

$$\text{EAU return margin} \begin{cases} y_{1,t} = 0.307 y_{1,t-1} \ *** + \varepsilon_{1,t} \\ h_{1,t} = 1.167 + 0.135 \varepsilon_{1,t}^2 \ *** + 0.853 h_{1,t-1}^2 \ *** \end{cases}$$

$$\text{BWI return margin} \begin{cases} y_{1,t} = 0.437 y_{1,t-1} \ *** + \varepsilon_{1,t} \\ h_{1,t} = 0.192 + 0.111 \varepsilon_{1,t}^2 \ *** + 0.862 h_{1,t-1}^2 \ *** \end{cases}$$

In the above specifications, *** indicates the statistical significance level of $p < 0.01$.

The GARCH model shows that the constants and coefficients for both EAU and BWI are significant, complying with the parameter assumptions. The residual error is then used for the DCC-GARCH(1,1) model analysis. Figure 3 shows the residual errors of GARCH(1,1). The traditional GARCH can only describe the variation of gathering effect (Francq and Zakoïan, 2010), but not the asymmetrical phenomenon, resulting in lower or higher estimates. According to the explanation of DCC-GARCH(1,1) by Engle (2002), the relative coefficients would vary as time changes. Figure 4 presents this result, the co-variant estimates changing with time, with EAU varying more than BWI. The DCC-GARCH(1,1) results are,

$EAU_t = 0.484 + 0.150 \times RESID1(-1)^2 + 0.557 \times GARCH1(-1)$

$BWI_t = 0.494 + 0.150 \times RESID2(-1)^2 + 0.556 \times GARCH2(-1)$

$COV1\_2 = 0.484 + 0.150 \times RESID1(-1) \times RESID2(-1) + 0.556 \times COV1\_2(-1)$

The correlation coefficient of the residual value estimated by the DCC-GARCH(1,1) model is 0.484.

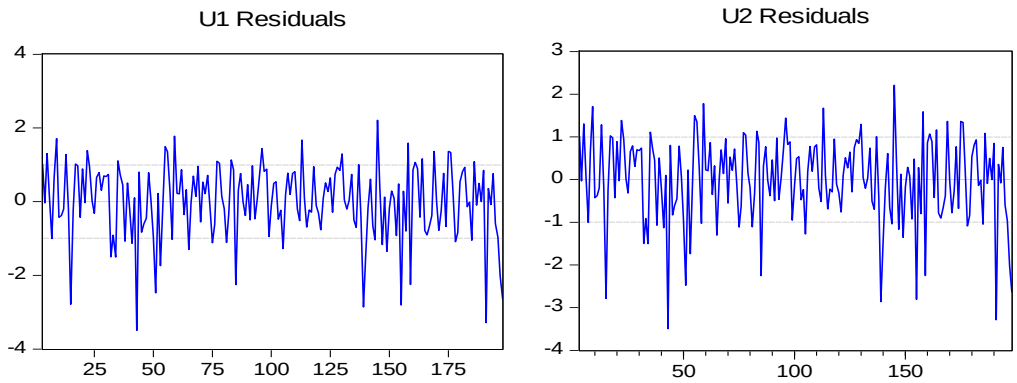

Figure 3 The residual value of EAU and BWI

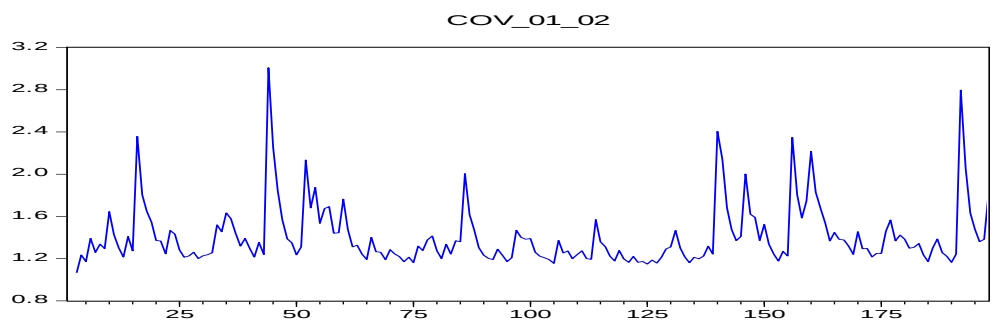

Figure 4 The co-variant estimates

5. Conclusions

In the past, correlation coefficients were the only means of understanding the relationship between different financial products, however certain errors might exist. As the related methodologies have evolved, correlation coefficients can vary with time. In order to improve the estimates or the hedging results, the dynamic correlation coefficients need to be investigated, in order to increase the effectiveness and reliability of the model. This research focuses on the EAU and BWI data series, applying the DCC model for the variation estimates. The empirical results show that,

1. When EAU has higher variation, so does the BWI. These variations show the gathering effect (Francq and Zakoïan, 2010), meaning a certain correlation between EAU and BWI.
2. The return margin and risk of EAU is larger than those of BWI, showing that EAU presents a high return margin and a high risk. The return margin and risk exhibit certain correlations.

3. According to Figure 1, EAU and BWI are both leptokurtic and asymmetric distribution. The coefficients of skewness for both EAU and BWI are lower than 0, meanwhile the coefficients of kurtosis are greater than 3.
4. The return margins of EAU and BWI are both static, based on the ADF results in Figure 2 showing the ADF unit root test time series data, and do not have the single root characteristics.
5. The correlation coefficient of the return margins for EAU and BWI is 0.484, meaning the dynamic correlation coefficients vary significantly for both EAU and BWI. Based on the data results, it can be seen that significant changes occur around every 6 weeks. The EAU and BWI are affected by different events at different times. The change of return margin for EAU is larger than for BWI.

This paper used the carbon trading price of the European market for the empirical analysis. As other countries, such as China and the United States, are developing the carbon trading markets the carbon market ought to experience certain degrees of impact. The carbon trading market also affects the carbon futures markets, hence, the current carbon price and future price as well as the hedging effect will emphasize this further. More industries will be included in the carbon trading market. Further research could investigate the risk of different carbon trading markets when the data are available.

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