INTERNATIONAL JOURNAL OF
COASTAL, OFFSHORE & ENVIRONMENTAL ENGINEERING

IJCOE Vol.1/No. 2/Transportation,
transit and maritime transport (50-56)

Dynamic spillover effect to manage ship fuel and crude oil portfolio using MGARCH model

Homayoun Yousefi
Associate Professor, Faculty of Economic and Management, Khorramshahr University of Marine Science and Technology, Khorramshahr – Iran, Email address: homayounyousefi@yahoo.com

ARTICLE INFO

Article History:
Received : 02June 2024
Accepted :10 Mar 2025

Keywords:
Optimum Hedging Ratio,
Ship Fuel, CCC Model, Crude Oil,
Fuel Price

ABSTRACT

Considering the existed uncertainty in fuel prices, a good risk management strategy is vital for the shipping companies as the other transport companies which are exposed to the mentioned fluctuations. In this regards, this article is aimed to calculate the optimum hedging ratio for the ship fuel in terms of minimum risk. Hence To account for the non-constant structure of return VAR-VECH model is applied. After the estimation the spillover and conditional structure of the variances can be built. These spillovers will be important in the risk calculation of any optional basket consisting two mentioned energy carriers. In the next step, Optimization process is performed by using the Lagrangian multiplier technique. The data are obtained from Bloomberg daily closing price of energy carriers for the spanning 10 years which started from January 2010 and ends to February 2019. Finally, results is to get the proportion of investment in both crude oil and ship fuel in a basket consisting these two energy carriers.

1. Introduction

Following the emergence of mega-corporations in one hand, and several political vicissitudes, Crude oil emerged as a strategic good in 1970s. So, the risk resulted from oil price movements necessitated a clear organism to discover oil real price and also to cover the price volatility risks. This lead to originate the oil stock market. It is also alleged that risk-averse investors prioritize the safety of principal over the possibility of a higher return. A high risk project drive it distractive for the potential investors unless it has an excessive return. Investors always consider risk-return trade off in their decision making in their portfolio choice. Since diversification will mitigate unsystematic risk, it's of great importance to choose a minimum risk portfolio given a specific return. This leads to the problem of selecting maximum utility portfolio which known as Markowitz or optimum portfolio.

2. Literature review

According to portfolio theory, risk and return could not be viewed separately**.** An individual stock performance is less important than how it impacts the entire portfolio. A stockholder can construct a portfolio of different assets that will maximize returns for a given level of risk. Similarly, given a desired level of expected return, he or she is to construct a least risk portfolio. For this reason, statistical measures such as variance and correlation is needed to compute the portfolio risk.

The expected return of the portfolio can be computed as a weighted mean of the each assets' returns. But The portfolio's overall risk is something more complicated, since it is a function of the variances of each asset plus the correlations of all possible pair of them.

Markowitz optimal portfolio model is also known as mean-variance model as it is based on the foundation of expected returns which is mean of returns and the standard deviation or variance of them in several alternative portfolios. The assumptions behind the Markowitz optimum portfolio is as follows:

– A portfolio overall risk is due to the variability of expected returns on different assets.
– Investor is assumed to be risk averse.
– Investor prefers to increase consumption possibility.
– Investor's utility function is concave and increasing, with respect to their risk aversion and consumption preference.

- Investor either maximizes its portfolio return for a given level of risk or minimizes its risk for a given return.
- Investor is rational in nature and prefer more utility to a less one.

All possible baskets that lie on the boundary of efficient portfolios are the ones with maximum return given a presumed risk and called the Efficient Frontier. All portfolios that lie under this Efficient Frontier are not as good because their expected returns would be lower for a given risk or likewise, investor should undertake a higher risk for a given desired return. In other words, this portfolio doesn't lead a risk averter investor to reach the maximum utility.

To obtain the Markowitz optimum portfolio one need to solve a linear programming:

$$Min \quad z = \delta_p^2$$

$$St \; : \delta_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \operatorname{cov}(\overline{r}_i, \overline{r}_j)$$

$$\sum_{j=1}^{n} w_j = 1$$

$$w_j > 0$$

In which:

w_i Is the share of ith asset in whole basket, $\overline{r}_p$ is folio overall portfolio expected return, $\overline{r}_i$ represents returns to ith asset and δ_p^2 is portfolio total risk and can be computed as follows:

$$\delta_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \operatorname{cov}(\overline{r}_i, \overline{r}_j)$$

Hence, to obtain the risk and returns of each basket one needs to estimate the structure (clearly mean, variances and co-variances) of individual assets return.

Several studies have been carried out in the field of variance and spillover effect. Some of them used univariate GARCH (Smolović and Lipovina; 2017, Paraskevi; 2017). Among the Reminder, most of them used multivariate GARCH, which some of the applied DCC(Billio et all; 2006, Piotr et al 2019) and some others specified a CCC GARCH model (Ledoit; 2003). However, to estimate a covariance structure between different assets, which is necessary in constructing optimal hedge ratios we should use a generalization to univariate mixed normal GARCH, that are multivariate GARCH models. Keighobadi and Ahmadi (2017) applied ARCH and GARCH model to compute value at risk. Keshavarzian et al(2013) studied the Discovery of the crude oil price fluctuations to disclose price change and reactions of these markets to the spillover in NYMEX. Moreover, it attempted to capture the fluctuation effects on the markets" instabilities and analyses the spot and future markets operations in both price discovery – through error correction model- or volatility and risk spillover – through multivariate GARCH-BRKK model. The results showed a unidirectional causality in mean equation which was from future to spot market but not vice versa. In other words, future markets undertake price discovery and is leader. The result of volatility spillover, information and risk transmission between markets showed that information transmission was from future to spot market and the reverse did not hold.

3. Research Methodology

To meet the researches aim, which is analyzing the spillovers between crude oil and ship fuel price returns, it is needed to estimate and analyze the spillover effect between different oil derives. For this reason, Multivariate GARCH model is selected to specify the relation between returns. This model is flexible in the lag selection and also the number of variables to be included in the model. More lags and variables make model more flexible to control for the dynamics of the covariance relations, but at the cost of less degree of freedom. So, lag selection criteria can be used to determine the optimum lag in a multivariate GARCH model in term of degree of freedom and also flexibility. Another condition which should be satisfied in a GARCH model is positive definiteness of covariance matrix. This property allows multivariate GARCH optimization to meet the second order condition.

3.1. Constant Conditional Correlation Model

This model is proposed by Bollerslev(1990) and gained most popularity among the M-GARCH models due to its simplicity and also the less number of parameter estimation. However it is not flexible as assumes the correlation between different assets are constant during the time. Hence, it is not capable of capturing interactions between assets in the model. An initial version of CCC model can be written as:

$$y_t = E\langle y_t \mid F_{t-1} \rangle + \varepsilon_t$$

$$\varepsilon_t = D_t \eta_t$$

(۴)

$$VAR\langle \varepsilon_t \mid F_{t-1} \rangle = D_t \Gamma D_t$$

Where, $y_t = (y_{1t}, ..., y_{mt})'$ and $\eta_t = (\eta_{1t}, ..., \eta_{mt})'$ `are two sequences of random vectors which are identically distributed. F_t Represents final information in time t,

$D_t = diag(h_t^{\frac{1}{2}},...,h_m^{\frac{1}{2}})$, m is the number of time intervals and $t=1,2,...,$ n is assumed to be constant. Finally, h_{it} $(i=1,...,m)$ follows a multivariate GARCH model:

(5)

$$h_t = \omega_t + \sum_{j=1}^{r} \alpha_{ij}\varepsilon_{i,t-j}^2 + \sum_{j=1}^{s} \beta_{ij} h_{i,t-j}$$

In which, α_{ij} is ARCH effect showing the short term shock persistency and β_{ij} are GARCH effect and imply long run persistency in the M-GARCH model.

3.2. Estimating M-GARCH model

Under the conditional normality assumption, one can estimate the parameters of M-GARCH model, which is mentioned in the former paragraph, by maximizing a likelihood function:

$$\ell(\theta) = -\frac{TN}{2}\log 2\pi - \frac{1}{2}\sum_{t=1}^{T}(\log|H_t| + \varepsilon_t^{'} H_t^{-1}\varepsilon_t)$$

(6)

In this model, θ represents all unknown parameters to be estimated. N is the number of oil future prices and is number of observations. An important point that should keep in mind is that all fluctuations must be considered relative to the mean and so the first step before estimation of covariance and correlations, is to model the mean of returns. However, we used a vector autoregressive model to estimate the mean equation.

4. Results and Discussion

Variables and Data

Spot and future's contract prices from West Texas Intermediate (WTI) is used in a daily basis in this empirical study. Also, ship Fuel prices extracted from Index Mundi website. The following formula is applied to calculate the returns on each fuel price.

$$R_t = \log(\frac{FP_t}{FP_{t-1}})$$

In which, FP_t are crude oil and ship fuel's future prices in time t, FP_{t-1} is this price but for the time t-1 and R_t is price return for the research variables. Our data spanned the period starting from 3rd January 2014 to 27th February 2020.

Table1 represents the descriptive statistics for both variables as well, including both the level and returns of the variables. According to table, in a level term, ship fuel has a larger mean and medium compared to crude oil price crude oil have had a relatively greater return. Moreover, except than crude oil price, rest of the series did not follow a normal distribution.

Table1: Descriptive Statistics

Statistic factors	Mean	Medium	Max	Min	Standard Dev	Skewness	Kurtosis	Jarque-Bera
Crude oil	75.32	80.12	151.82	19.33	15.73	-0.03	2.76	0.89
Ship Fuel	126.43	134.64	282.13	35.28	2.01	1.08	3.45	201.98
Rcrude	0.00012	0.00020	0. 12	-0.130	0.011	0.002	4.25	708.11
R Ship	0.0004	0.0004	0.153	-0.137	0.062	1.028	7.003	193.990

Source: research findings

4.1. Stationarity test

Stationarity is not a crucial precondition before estimating a M-GARCH model. However as we run a VAR model for the mean equation, it is necessary to examine unit root to ensure whether the series are co integrated or not. Time series graphs are plotted for the initial intuition.

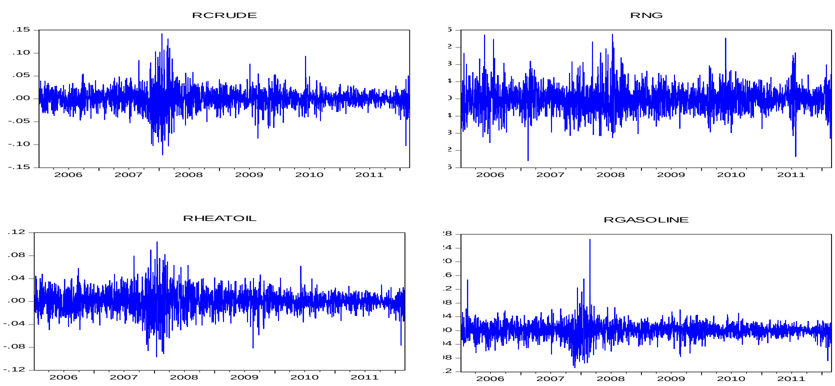

Figure 1. Time series graphs of the variables.

As it can be easily seen, all four graphs can provide a visual evidence that time series doesn't have a deterministic trend. Recalling that stability condition necessitates that series must have constant mean and variance during the time, it is less likely for the series to have a unit root. But to make sure about stationarity, an augmented Dicky-Fuller and a Philips- Peron test is adopted in table2:

Table2. Unit root tests (Augmented Dicky-Fuller and Philips Peron)

Series name	Level		
	Trend and Intercept	Intercept	None
Crude oil	-35.614	-35.593	-35.640
Ship Fuel	-25.276	-25.082	-25.437
1% Critical Value	-3.430	-3.96	-2.56
5% Critical Value	-2.86	-3.41	-1.94
10% Critical Value	-2.56	-3.12	-1.61

It is clear that both series are statistically stationary in all 1% significance level.

4.2. Model Estimation

As said former, a VAR parametrization should be run in the first step. Hence, the optimal lag is examined using different lag selection criteria. As different information criteria suggested, our VAR specification is estimated using 1 period lag and then squared errors are ready to input in the GARCH model in the next step. Table7 shows CCC-VAR results using one period lag between crude oil and Ship Fuel returns.

Table3. Model Estimation

Covariance: R. Crude-R ship	R Ship Fuel	R crude	Var(1)
-	-0.0134* (0.072)	-0.0121** (0.035)	R crude(-1)
-	-0.0373** (0.009)	-0.1139** (0.011)	R Ship Fuel (-1)
-	0.0004*** (0.0001)	0.0035*** (0.0017)	Constant
-	0.1911** (0.0441)	0.319** (0.045)	α
-	0.8029* (0.0589)	(0.706)* (0.01012)	β
-	0.994	0.945	$\alpha+\beta$
0.72687** (0.0191)	-	-	Constant conditional correlation

The numbers in parentheses indicate standard errors. *** 1% significance. ** 5% significance and * 10% significance.

In this model, α represent short persistence which is by far higher in crude oil return than Ship Fuel return. ARCH effects (α) are smaller than the GARCH coefficients (β) and are both significant at 5%. Also, long memory for two series found to be close to zero, indicating the long persistence of volatility shock. Also, conditional covariance between two energy carriers is nearly 0.727 and significant at 5% level.

5. Conclusion

In this paper, to construct an optimum two fuels portfolio, the spillover effect and the volatility structure of two important fuel, namely Crude oil and Ship Fuel, price returns is analyzed applying a two-step procedure. Firstly, we run a VAR model to estimate the mean equation. In the next step, using the squared errors obtained from mean equation, a CCC GARCH model is estimated. Results suggested that almost all of parameters were significant at 5% and was in line with the previous findings. Moreover, a relatively large positive value for the constant conditional correlation between suggest the possibility of cross hedging between two fuels. Following Kroner and Ng (1998) one can use this coefficient to construct the Markowitz portfolio, in which the weights of both assets are optimum. The optimum weights in this model is:

$$w_{12,t} = \frac{h_{22,t} - h_{12,t}}{h_{11,t} - 2h_{12,t} + h_{22,t}}$$

و

$$w_{12,t} = \begin{cases} 0 & \text{اگر} & w_{12,t} < 0 \\ w_{12,t} & \text{اگر} & 0 \le w_{12,t} \le 1 \\ 1 & \text{اگر} & w_{12,t} > 1 \end{cases}$$

Where, $w_{12,t}$ is the optimum weight of future crude oil in portfolio in time t. $h_{12,t}$ is conditional correlation between crude oil and Ship Fuel. $h_{22,t}$ Stands for conditional variance of Ship Fuel, and finally, the optimum weight of Ship Fuel to buy in spot market would be $1-w_{12,t}$. So, based on the results of CCC-GARCH model, airlines risk of ship fuel price fluctuations would be minimize if they hedge 34% of their Ship fuel with holding crude oil future contract.

6. References

1. Agboola, S., Olusegun, A, M(2017), Relationship between Nigeria Stock Exchange and Inflation to Dynamic Conditional Correlation Model, Journal of Statistics Applications & Probability Letters, No. 2, 51-56.
2. *Alalaya, M(2014,* A Case Study: Study of Amman Stock Exchange Volatility during 1994–2013, I nternational Business Research, Vol7, No5, pages: 213-229.
3. Basher, S, A, Sadorsky, P(2016), Hedging emerging market stock prices with oil, gold, VIX, and bonds: A comparison between DCC, ADCC and GO-GARCH, Energy Economics, v24, pages: 235-247.
4. Bauwens , B., Laurent, S and Rombouts, J (2006), Multivariate GARCH models: a survey, Journal of Applied Econometrics, Volume21, Issue1, Pages 79-109.
5. Billio ,M., Caporin , M & Gobbo, M (2006) , Flexible Dynamic Conditional Correlation multivariate GARCH models for asset allocation, Applied Financial Economics Letters , 2(2), 123-130.
6. Bollerslev, T. (1990), Modeling the coherence in short-run nominal exchange rates: a Multivariate generalized ARCH model. Review of Economics and Statistics, 72, 498-505.
7. Bunnag, Tanattrin, Hedging Petroleum Futures with Multivariate GARCH Models, International Journal of Energy Economics and Policy, Vol. 5, No 1, 2015, pp.105-120.
8. Chia-Lin Chang & Michael McAleer & Roengchai Tansuchat, 2010. "Crude Oil Hedging Strategies Using Dynamic Multivariate GARCH," KIER Working Papers 743, Kyoto University, Institute of Economic Research.
9. Chang,C, L., McAleer, M., Tansuchat, R(2011), Crude oil hedging strategies using dynamic multivariate GARCH, Energy Economics, Volume 33, Issue 5, Pages 912-923.
10. Edgars Jakobsons, E (2016), Suboptimality in Portfolio Conditional Value-at-Risk Optimization, Journal of Risk, Vol. 18, No. 4, PP: 41-65.
11. Khaleghi, M, F., Dehghan, D, H and Sadeghian, A(2014), Portfolio Optimization by Using Birds Flight Algorithm, Vol4, No 2, pages: 334-342.
12. Kroner, K.F., Ng, V.K. (1998), Modeling Asymmetric Comovement of Asset Returns. Review of Financial Studies, 11, 122-150.
13. Keyghobadi, A., Ahmadi, M(2017) comparing the efficiency of the GARCH and ARCH methods in referencing VAR for optimal portfolio selection, Journal of financial accounting and auditing researches ,8(32), 63-82.
14. Keshavarzian, M., Raghfar, H., Khiabani, N, Jalali, N, A (2013), Casuality and volatility spillover between spot and future oil market: case of Nymex, Journal of Monetary and Financial Economics, 20(5), 136-163.
15. Lee, C,F., Bin, J,S(2012), Alternative statistical distributions for estimating value-at-risk: theory and evidence, Review of Quantitative Finance and Accounting, Volume 39, Issue 3, pp 309–331.
16. Ledoit, Olivier, SANTA-CLARA, Pedro & Wolf, Michael (2003). Flexible Multivariate GARCH Modeling with an Application to International stock Markets. The Review of Economics and Statistics, Vol. 85, pp.735–747.
17. Mikkonen, T (2017), Time -varying conditional correlation:Effect on international portfolio diversification in Southeast Asia, M.A Thesis, University of Jyväskylä.
18. Pojarliev M., Polasek W. (2003) Portfolio construction by volatility forecasts: does the covariance structure matter?. Financ. Mark. Portf. Manag. 17(1): 103–116.
19. Piotr, F., Marcin, F., Peter, M (2019) Range-based DCC models for covariance and value-at-risk forecasting, Journal of Empirical Finance, 54(3), 58-76.
20. Ranković, V., Drenovak, M and Urosevic, B(2016), Mean-univariate GARCH VaR portfolio optimization: Actual portfolio approach, Computers & Opderations Research, Volume 72, Pages 83-92.
21. Paraskevi, K(2017) Volatility estimation for Bitcoin: A comparison of GARCH models, Economics Letters, 158, 3-6.
22. Saltik,O.,Degirmen,S & Ural, M(2016), Volatility Modelling In Crude Oil and Natural Gas Prices. Procedia Economics and Finance 38 476 – 491.
23. Smolović, J, C., Lipovina, M(2017), T1 - GARCH models in value at risk estimation: empirical evidence from the Montenegrin

stock exchange, Economic Research, 30(1), 477-498.

24. Tsui, Q and yu, Q (1999), Constant Conditional Correlation in a Bivariate GARCH Model: Evidence from the Stock Markets of China, Mathematics and Computers in Simulation, 48(4-6):503-509.
25. Tamvakis,M., Lin,X(2001), Spillover effects in energy futures markets, Energy Economics, Volume 23, Issue 1, Pages 43-56.