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Original article

# Study of Volatility of New Ship Building Prices in LNG Shipping*

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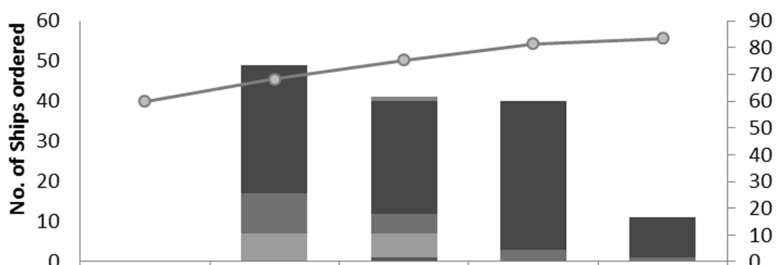
**Abstract**

The natural gas market has been expanding in size and has attracted particular attention across the global energy market. Although most natural gas transportation is carried out through pipelines, almost one third of it is done with the help of merchant vessels, capable of carrying liquefied natural gas. These LNG carriers have a special design and thus can be treated as a separate class of global fleet. New vessels are huge capital investments by vessel owning companies and just like other vessel classes; the new shipbuilding prices for the LNG segment continue to be a key aspect in the decision making of business players. Additionally these prices can be volatile as new ship building prices fluctuate with time. This paper attempts to analyse the volatility of new ship building prices of LNG carriers. For the study, the average ship building prices for all the LNG carriers having volume carrying capacity is between 160,000 – 173,000 cbm to be delivered between 2016 – 2019 were taken into account. For the analysis, GARCH and EGARCH methods were applied on the data set. The analysis concluded that there is a great deal of volatility in the new ship building prices of LNG vessels. It was also identified that negative shocks were more persistent the positive shocks.

*Keywords:* “Ship building, LNG shipping, Price volatility, GARCH, EGARCH”

## I. Introduction

In January 1959, the Methane Pioneer delivered the first-ever transoceanic cargo of LNG, from the U.S. Gulf Coast to the United Kingdom (Justine Barden, 2014). The success of LNG transportation, shipping demand and profitability by LNG tankers attracted ship-owners to order new LNG vessels. As a result of increased orders for LNG tankers and technological advancements LNG ship building capacity has intensified in recent years.With developments in LNG ship building, the volume of transportation has increased significantly. In 2004, the global LNG shipment volume stood at 163 billion cubic meters (United Nations Conference on Trade and Development, 2005), which then increased to 333.3 billion cubic meters in 2014 (United Nations Conference on Trade and Development, 2015), an increment of 48%. However, the future of the LNG carriage by sea is bright as the BP Energy Outlook 2035 is projecting that natural gas will overtake oil as the world's dominant fuel source and will account for almost a third of all primary energy by 2035 (Inkson, 2015). Thus by the end of 2019, 143 more vessels are going to join global LNG fleet, to meet the growing demand (International Gas Union, 2016). An analysis of new LNG vessel order book indicates that 95% of new order vessels are of a conventional ship type and rest are Floating Storage Regasification Units (FSRU). The increment in capacity and vessel count of the world fleet can be analyzed in Figure 1.




| | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|
| >180000 | | | 1 | | |
| 170001-180000 | | 32 | 28 | 37 | 10 |
| 160001-170000 | | 10 | 5 | 3 | 1 |
| 150001-160000 | | 7 | 6 | | |
| <150000 | | | 1 | | |
| Global Fleet Capacity in MMCM | 60 | 68.3 | 75.3 | 81.5 | 83.4 |

**Figure 1: LNG Vessel Order Book (2016-2019)**
Source: (Union, 2015) (LNG, 2016)

Like other business domains, decision making is a critical thought process, which leads to business growth and ensures profitability in the segment. Considering cyclic movement of the industry, ship owners may decide to expand their fleet size by ordering new ships, when the market demand is high. With high demand for carriages, new ship building orders increase and result into higher ship building prices. Additionally prices, correlate strongly with freight rates and together with them, fluctuate widely (Haralambides, Tsolakis, & Cridland, 2004). The timing of the investment is therefore the single most important factor for business success. Thus, LNG vessel owners must monitor the growth in demand and ship building prices to leverage the most out of their investments. However, the volatility in new ship building prices may render hesitant decision making by ship owners. Since LNG shipping has been expanding due to an increase in new ship orders, market players need to understand new LNG ship building prices and what drives them over a period of time.

Another critical aspect to consider when ordering a new ship is to identify the most suitable volume and most suitable carrying class of vessel, as the industry requires high capital and time to deliver a single vessel. There are several drivers like individual business models, specific demand, technology etc. which may influence the ship owner's choice of carrying class. Looking at global LNG fleet which comprises of 410 active vessels (International Gas Union, 2016), about 81 % have a volume carrying capacity between 125,000 to 175,000 cbm. Similarly, only 15% of vessels active in fleet are between 160,000 to 173000 cbm. However an examination of the LNG ship order book (International Gas Union, 2016), reveals that 31 % of all ordered ships until 2019 will be between 160,000 to 173000 cbm. The major driver for such a change in the volume carrying class is a result of the upcoming Panama Canal expansion, which will be able to accommodate LNG ships of up to a 1,80,000 cbm capacity (Justine Barden, 2014). Thus it can be concluded that in near future, LNG shipping and its global fleet will be modified with special focus on developing a volume carrying class of approximately 160,000 to 175000 cbm.

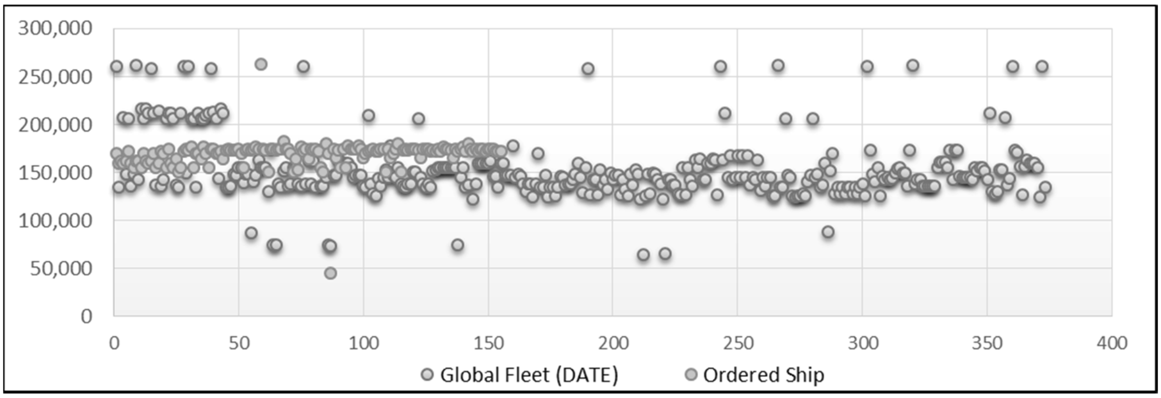



**Figure 2: LNG Global Fleet by 2019**
Source: (Union, 2015) (LNG, 2016)

In order to identify and examine volatility, GARCH models have been widely used across several business models including shipping. However their application in LNG shipping market limited. Thus the paper attempts to apply GARCH (1,1) on new LNG shipbuilding prices and to examine its volatility. For this purpose, a focused class of LNG vessels with volume carrying capacity between 160,000 to 173000 cbm has been considered suitable.

**II. Literature Review**Apart from theory of demand and supply to understand new ship building prices, Asset pricing method have been used in early studies. (M Beenstock, 1985), examined the determinants of ship prices and he argues that ship prices cannot be appropriately analyzed by a theory of demand and supply. His contribution to literature along with A. Vergottis, (Michael Beenstock & Vergottis, 1989a, 1989b, 1993) consists of several papers on how to model a new ship building market using the asset pricing method and they argue over the need for new ship building prices to be correlated to second hand ship prices. However the argument has been challenged by author (Haralambides et al., 2004) who states that secondhand prices are volatile whereas new prices are relatively sticky and the two prices are not perfectly correlated. Besides this, a lot of research has been done on new- building and secondhand vessel price modeling. Specific econometric models have been formed to estimate new building and secondhand vessel prices. The new build vessel price and freight rates have been confirmed to have the largest impacts on secondhand vessel prices; while trading volume and trading activity can also affect vessel prices (Adland & Koekebakker, 2007; Alizadeh & Nomikos, 2003; Tsolakis, Cridland, & Haralambides, 2003). (Jiang & Lauridsen, 2012; Lun & Quaddus, 2009; Mulligan, 2008; Xu, Yip, & Liu, 2011) examined the dynamic relationship between international sea freight rate and new build price by employing panel co-integration testing and estimation techniques. As a result of this, the authors found a positive directional relationship from freight rate to the new build price.

A number of author groups have looked at on new ship build price volatility from different perspectives. . Traditional models such as ARIMA, ADF were applied to study freight rate volatility (Cullinane, 1992) (Albert William Veenstra; Philip Hans Franses, 1997). However, (Manolis G. Kavussanos, 1996; Manolis G Kavussanos, 1996) first applied ARCH (Auto Regressive Conditional Heteroscedasticity) classic models into the shipping market. Kavussanos's contribution examines the effectiveness of volatility in the dry and tanker ship market using the ARCH model and made arguments about the relationship between volatility and different classes of dry cargo vessels. FIGARCH model has also been used to model the volatility for wet bulk and dry bulk freight rates (N Nomikos, 2009). (Dai, Hu, Chen, & Zheng, 2015) using GARCH (1,1) revealed that in a dry bulk segment, freight rate volatility is the most important determinant for the new build price volatility taking in account the capesize, panamax, handymax and handysize sectors.

From the above literature review, we find that the ARMA model cannot foresee the future return because of constant variance. Hence, GARCH time series models are better for modelling the non-constant volatility. The ARCH (1) model is the simplest GARCH model and similar to the AR (1) model i.e. conditional variance has a structure very similar to the conditional exception in an AR model. ARCH term only captures information about volatility from the previous period by measuring the lag of the squared residual from the mean equation, but does not considers last period error variance forecast Though the GARCH model captures the volatility clustering, it doesn't capture the leverage effect. In order to capture leverage effect EGARCH models can be applied. (Baillie, Han, Myers, & Song, 2007) in their studies about long memory refer to the presence of a slow hyperbolic decay in the autocorrelations and impulse response weights. Hence (Baillie, Bollerslev, & Mikkelsen, 1996) proposed FIEGARCH (p,d,q) and (Baillie et al., 1996) proposed FIEGARCH (p,d,q) models. Asymmetric and leverage effects can be found using FIEGARCH. (Jin & Frechette, 2004) studied the presence of fractional integration in the volatility for the future of agricultural prices using data from 1970 to 2000. However the sample size used in this study is not sufficient to capture long term memory using FIGARCH and FIEGARCH models. Hence this study uses the GARCH model to measure and confirm the persistence of volatility and EGARCH model to capture the leverage effect.

### III. Data Gathering

For the study, a specific class of LNG vessels with a volume carrying capacity of between 160,000 to 173000 cbm have been considered. This class has been chosen because after expansion and reopening of the Panama Canal, LNG carriers with capacity up to 180,000 cbm can pass through it. The identified class is applied as a filter on the global LNG new vessel order book. For modelling new LNG ship building price volatility, 126 observations in form of monthly prices from April 2005 to August 2015 are examined in this time series. The new ship building prices were collected from Drewry Maritime Consultants, India.

### IV. Data Analysis

For the analysis GARCH (1, 1) model is used which is a type of GARCH (p,q) model. The GARCH (p,q) model of (Bollerslev, 1986) includes p lags of the conditional variance in the linear ARCH(q) conditional variance equation. A simple GARCH (1, 1) equation can be expressed as-

$$\sigma_t^2 = \omega + \alpha\ \eta_{t-1}^2 + \ \beta\sigma_{t-1}^2 \tag{1}$$

The GARCH model successfully brings forth the volatility clustering, but it is an inadequate model when we wish to analyze the leverage effect. This is because the conditional variance is a function only of the magnitudes of the past values, but it does not capture whether the effect is positive or negative. This asymmetric relationship is called the leverage effect. This describes how a negative shock causes more volatility than a positive shock even if the same magnitude had occurred. Different models have been used to capture this asymmetry. EGARCH model captures asymmetric responses of the time-varying variance to shocks and also ensures that the variance is always positive. The model was developed by (Nelson, 1991).

$$\log\sigma_t^2 = \omega + \sum_{i=1}^{q}\left(\alpha_i\,\eta_{t-i} + \ \gamma(|\eta_{t-i}| - E|\eta_{t-i}|)\right) + \sum_{i=1}^{q}\log\sigma_{t-j}^2) \text{ and } \epsilon_t = \sigma_t\eta_t \tag{2}$$

The left-hand side is the log of the conditional variance in equation (2). The equation implies that the leverage effect is exponential, rather than quadratic and that the forecast of the conditional variance is guaranteed to be non-negative. The presence of leverage effects can be tested by the $\gamma_i < 0$ . The impact is asymmetric if$\gamma_i \neq 0$. The equation (2) also explains the conditional variance where the generating process for the natural algorithm of conditional variance is defined. The EGARCH stresses the asymmetric function of past innovation shocks. γ is referred to as the magnitude of persistence of variance. The nearer the magnitude approaches to unity, the greater would be the persistence of shocks towards volatility. The negative and positive shocks anticipates excess, the returns determine the future variance measured by α and β. Here α is the magnitude effect and if α > 0, then innovation in log (σ) is then positive when magnitude of (σ-j) is larger than its expected value and vice versa. β is a sign of effect and if β = 0, then there is non-existence of asymmetric volatility. If β < 0 and statistically significant, the volatility of the return shock is asymmetric and the negative volatility impactis larger than the same magnitude of positive shocks. Thus the negative β represents the persistence of leverage effect.

For the simple version of the Dickey-Fuller test, we assume that

$$Y_t = \alpha + \beta t + \varphi Y_{t-1} + \epsilon_t \qquad (3)$$

and we would like to test if $\varphi = 1$

We can write the previous representation as

$$\Delta Y_t = \alpha + \beta t + [\varphi - 1] Y_{t-1} + \epsilon_t \qquad (4)$$

The time series converges to a stationary if time series if |φ| < 1. If |φ| = 1, the time series is not stationary (Random walk) and if > 1, the variance grows exponentially as the time period increases.

**Table 1: New Ship Building Prices**

| | |
|---|---|
| ADF Test Statistic | -11.1455 |
| Critical Value (99%) | -2.575829 |
| Critical Value (95%) | -1.959964 |
| Z – Lag 1 Coefficient | -1.00494 |
| Standard Error | 0.09017 |
| t value | -11.15 |
| Pr(>\|t\|) | <2e-16 |
| Residual standard error | 0.01798 on 123 degrees of freedom |
| Multiple R-squared | 0.5025 |
| Adjusted R-squared | 0.4984 |
| KPSS Test Statistic | |
| Value of test-statistic | 0.1375 |
| Critical Value (99%) | 0.739 |
| Critical Value (95%) | 0.463 |

Source: Author's own analysis

**ADF Test**

ADF test goes with a null hypothesis that $|\varphi| = 1$ and the time series is not stationary. If the value of the statistic < 99% critical value, then the series is stationary. If the value of the statistics exceeds those critical values, then the series is not stationary. In this case for each of the three time series data, the ADF test statistic value is < Critical value at 99% indicating that all the three time series are stationary. The same is confirmed through p-value (<2e-16).

**KPSS Unit Root Test**

Null hypothesis is Stationarity. If the value of the test statistic < Critical value, the series is stationary. In this case, the value of the test statistic < Critical value for 99% as well as 95% indicating that all the three series are stationary

Hence it can be quite comfortably concluded that the three time series data are stationary.

**Volatility clustering**

Volatility clustering is a phenomenon where there are relative calm periods and periods of high volatility. This situation is very much a universal attribute of market data. GARCH (Generalized Auto Regressive Conditional Heteroscedasticity) is used to model volatility clustering. The GARCH view is that volatility spikes upwards and then falls until there is another spike. The estimation of a GARCH model is mostly about estimating how fast the downturn is. If you have fewer than 1000 daily observations, then the estimation is unlikely to give you much real information about the parameters. We are staying with a GARCH (1, 1) model; not because it is the best — it certainly is not. We are staying with it because it is the most commonly available GARCH models are almost always estimated via maximum likelihood. This turns out to be a very difficult optimization problem.

**Autocorrelation**

If the volatility clustering is properly explained by the model, then there will be no autocorrelation in the squared standardized residuals. It is common to do a Ljung-Box test to test for this autocorrelation.

**Persistence**

The persistence of a GARCH model has to do with how fast large volatilities decay after a shock. For the GARCH (1,1) model the key statistic is the sum of the two main parameters (alpha1 and beta1). The sum of alpha1 and beta1 should be less than 1. If the sum is greater than 1, then the predictions of volatility are explosive — we are unlikely to believe that. If the sum is equal to 1, then we have an exponential decay model.

The general process for a GARCH model involves three steps. The first is to estimate a best-fitting autoregressive model; secondly, to compute autocorrelations of the error term and lastly, to test for significance alpha1 measures the extent to which a volatility shock of the current period feeds through into next period's volatility and alpha1+beta1 measures the rate at which this effect dies over time.

*4.1. New Ship Building Prices*

**Table 2: Optimal parameters of the model**

| | Estimate | Std. Error | t Value | Pr(>\|t\|) |
|---|---|---|---|---|
| **Mu** | -0.000174 | -2.575829 | -0.099993 | 0.92035 |
| **Omega** | 0.000000 | -1.959964 | 0.000000 | 1.00000 |
| **alpha1** | 0.000057 | -1.00494 | 0.061001 | 0.95136 |
| **beta1** | 0.990211 | 0.09017 | 448.890967 | 0.00000 |

Source: Author's own analysis

From the results, it is clearly evident that the sum of alpha1 and beta1 is 0.990268 < 1 indicating there is a mean reversion in the process. Since the sum is very close to 1, the reversion process is pretty slow. This also indicates that the weightage for Long term volatility based on long term rates is 0.97% (1-alpha1-beta1) so the variance prediction model gives 0.0057% weightage to the latest squared error term (deviance of returns from the mean), 99.02% weightage to the variance based on the squares of previous time periods' and 0.97% for long term average volatility. Based on the omega, the mean reverting value of the variance is 0.000000/0.009732 = 0.0 and a monthly standard deviation of 0%. However the p-values of beta1 only are less than 0.05 indicating the inconsistency in the values of alpha1 and omega being significantly different from 0. Other versions of GARCH can be evaluated for the same.

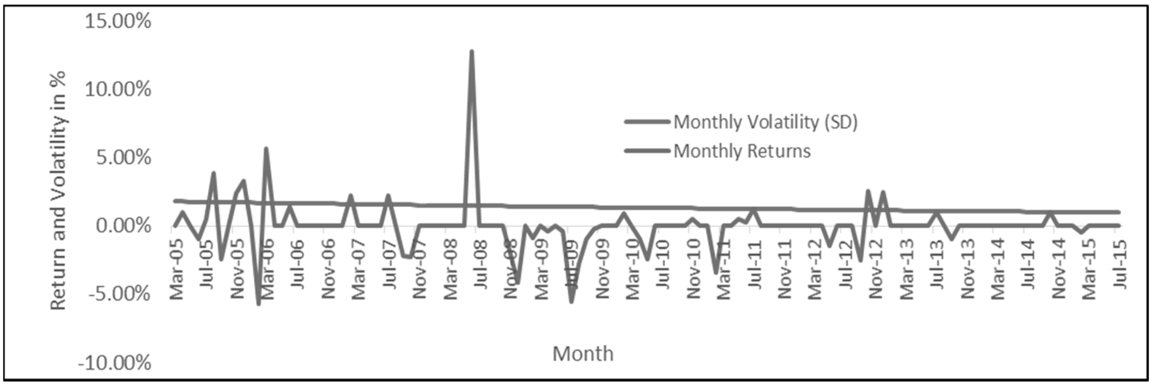



**Figure 3: Monthly Returns vs. GARCH (1,1) volatility of NB Prices**
Source: Author's own analysis

**Table 3: Weighted ARCH LM tests**

| Weighted ARCH LM | Statistic | Shape | Scale | P-Value |
|---|---|---|---|---|
| | 0.0733 | 0.5 | 2 | 0.7866 |
| **ARCH Lag[5]** | 0.2089 | 1.44 | 1.667 | 0.9634 |
| **ARCH Lag[7]** | 0.5874 | 2.315 | 1.543 | 0.9698 |

Source: Author's own analysis

This is used for testing the null hypothesis of adequately fitted ARCH process. This test can be performed after fitting an ARCH process to a time series. The p-values for each of the lags are above 0.05 indicating that for this data, the ARCH process is an adequate fit.

**Table 4: Weighted Ljung Box Test on Standardized Residuals and Standardized Squared Residuals**

| **Weighted Ljung Box Test on Standardized Residuals** | | |
|---|---|---|
| | **statistic** | **p-value** |
| **Lag[1]** | 0.02182 | 0.8826 |
| **Lag[2*(p+q)+(p+q)-1][2]** | 0.03623 | 0.9672 |
| **Lag[4*(p+q)+(p+q)-1][5]** | 0.31755 | 0.9819 |
| | | |
| **Weighted Ljung Box Test on Standardized Squared Residuals** | | |
| | **statistic** | **p-value** |
| **Lag[1]** | 0.0004628 | 0.9828 |
| **Lag[2*(p+q)+(p+q)-1][5]** | 0.2076487 | 0.9920 |
| **Lag[4*(p+q)+(p+q)-1][9]** | 0.5888449 | 0.9974 |

Source: Author's own analysis

The p-values of >0.05 clearly indicate that there is no auto correlation among the standardized residuals as well as standardized square residuals for different lags. This volatility clustering is aptly explained by the model.

**Table 5: Likelihoods and Information Criteria**

| | |
|---|---|
| **LogLikelihood** | 334.2808 |
| **Akaike** | -5.2845 |
| **Bayes** | -5.1940 |
| **Shibata** | -5.2865 |
| **Hannan-Quinn** | -5.2477 |

Source: Author's own analysis

GARCH model assume that only the magnitude of unanticipated excess returns helps in determining the result. In reality, not only the magnitude but also the direction of the returns affects volatility. Negative shocks (events/news, etc.) tend to impact volatility more than positive shocks. Using this model, we can expect a better estimate for the volatility of asset returns due to how the EGARCH counteracts the limitations based on the classic GARCH model.

The years 2007 to 2009 saw high number of new LNG vessel deliveries to the LNG shipping market. However, the same period experienced a record low in number of orders for new LNG vessels. The year 2008 also saw a global financial meltdown. The news resulted in negative price volatility in the months of July and August 2008. This was also followed by more negative shocks of a smaller magnitude which can be observed in figure 3 and figure 4.

EGARCH models attempt to address volatility clustering in an innovative process. Volatility clustering occurs when such process does not exhibit significant autocorrelation, but the variance of the process changes with time. EGARCH models are appropriate when positive and negative shocks of equal magnitude may not contribute equally to volatility. Model posits that the current conditional variance is the sum of these linear processes:

- Past logged conditional variances (the GARCH component or polynomial – beta1)
- Magnitudes of past standardized innovations (the ARCH component or polynomial – alpha1)
- Past standardized innovations (the leverage component or polynomial – gamma1)

*4.2. New Ship Building Prices Returns*

**Table 6: Optimal Parameters**

| | Estimate | Std. Error | t Value | Pr(>\|t\|) |
|---|---|---|---|---|
| **Mu** | -0.000174 | 0.001286 | 3.4283 | 0.000607 |
| **Omega** | 0.000000 | 0.054331 | -4.3741 | 0.000012 |
| **alpha1** | 0.000057 | 0.043703 | 2.3188 | 0.020406 |
| **beta1** | 0.990211 | 0.140552 | 6.9117 | 0.000000 |
| **gamma1** | 0.990211 | 0.066240 | -2.7942 | 0.005202 |

Source: Author's own analysis

For the data given above, the alpha value is 10.13% indicating that a positive weightage is given to the recent observations, a value of 97.14% to beta1 indicates a very high weightage being given to the volatility contributed to by the past few periods and a negative 18.51% to gamma indicates a weightage given towards leverage (Negative shocks contributing more to the volatility corresponding to the positive shocks). The p-values corresponding to all the coefficients are <0.05, indicating that all the coefficients are significant at 5%. The volatility is increasing drastically when there is a big reduction in the prices compared to an equal increase in the price.

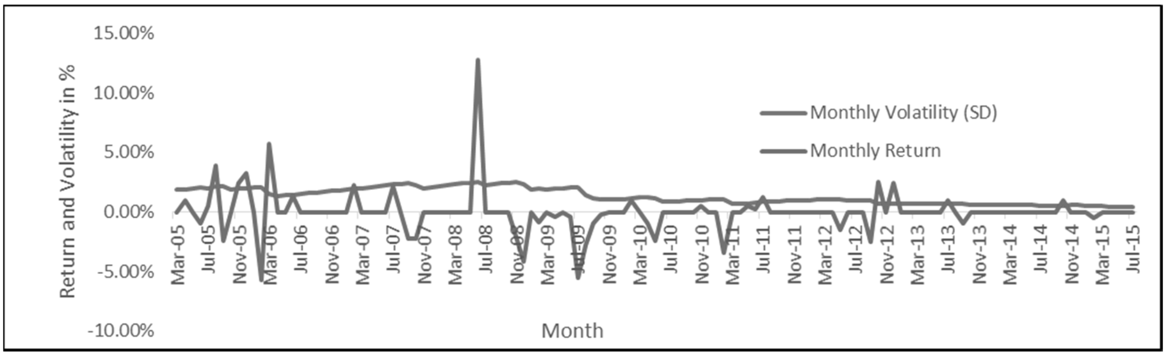



**Figure 4: Month Returns vs. E-GARCH volatility of NB Prices**
Source: Author's own analysis

**Table 7: Likelihood and Information Criteria**

| | EGARCH | GARCH |
|---|---|---|
| **LogLikelihood** | 361.7645 | 334.2808 |
| **Akaike** | -5.7082 | -5.2845 |
| **Bayes** | -5.5951 | -5.1940 |
| **Shibata** | -5.7113 | -5.2865 |
| **Hannan-Quinn** | -5.6623 | -5.2477 |

Source: Author's own analysis

The log-likelihood value is higher for EGARCH compared to GARCH. The higher the Log Likelihood, the better the model is for comparison purposes. Hence EGARCH is a better model compared to GARCH. The other 4 information criteria specified (Akaike, Bayes, Shibata, Hannan Quinn) are lower for EGARCH compared to GARCH which also stress the same point that EGARCH is the better of the two models for modelling volatility for this data set

**Table 8: Weighted Ljung-Box Test on Standardized Residuals**

| **Weighted Ljung-Box Test on Standardized Residuals** | | |
|---|---|---|
| | Statistic | p-value |
| **Lag[1]** | 0.0302 | 0.8620 |
| **Lag[2*(p+q)+(p+q)-1][2]** | 0.6164 | 0.6414 |
| **Lag[4*(p+q)+(p+q)-1][5]** | 1.4734 | 0.7465 |

Source: Author's own analysis

**Table 9: Weighted Ljung-Box Test on Standardized Squared Residuals**

| **Weighted Ljung-Box Test on Standardized Squared Residuals** | | |
|---|---|---|
| | Statistic | p-value |
| **Lag[1]** | 0.907 | 0.3409 |
| **Lag[2*(p+q)+(p+q)-1][5]** | 1.635 | 0.7068 |
| **Lag[4*(p+q)+(p+q)-1][9]** | 2.398 | 0.8526 |

Source: Author's own analysis

The p-values of >0.05 clearly indicate that there is no auto correlation among the standardized residuals as well as standardized square residuals for different lags. This volatility clustering is aptly explained by the model.

**Table 10: Weighted ARCH LM Tests**

| **Weighted ARCH LM Tests** | | | | |
|---|---|---|---|---|
| | Statistic | Shape | Scale | P-Value |
| **ARCH Lag[3]** | 0.09513 | 0.500 | 2.000 | 0.7578 |
| **ARCH Lag[5]** | 1.25970 | 1.440 | 1.667 | 0.6577 |
| **ARCH Lag[7]** | 1.52290 | 2.315 | 1.543 | 0.8168 |

Source: Author's own analysis

This is used for testing the null hypothesis of the adequate ARCH process. These tests can be performed after fitting an ARCH process to a time series. The p-values for each of the lags are above 0.05 indicating that for this data, ARCH process is a tolerable fit. .

## V. Conclusion

Like other markets, in shipping, players need to develop a decision making ability to take and manage risk in order to realize long term profitability. This can be achieved by considering; the delivery time of new LNG ship orders, the demand for LNG trade and price fluctuation. The demand for LNG vessels in the near future is predicted to be high since USA and Australia are planning to boost their exports by 2018 which in turn will increase the shipping miles for LNG. Ship owners can capitalize on this high demand scenario and use it as an opportunity to invest in their fleet portfolio.

But the results from EGARCH analysis on new shipbuilding prices of LNG vessels indicate that carrier owners need to be cautious in their fleet expansion as ship owner's return on new build LNG vessel may vary asymmetrically. From the results the significance of persistent negative shocks or the volatility asymmetry indicates that the ship owners are more likely to be affected by the negative news as compared to the positive news. This implies that the volatility spill over the mechanism is asymmetric. Results of the study also indicate that the future of high volatility is associated with low returns and high future expected returns. Therefore rather than ordering the new vessels hastily, ship owners need to wait and be cautious in order to avoid the risk of high and low returns due to the negative shocks in the LNG shipbuilding prices.

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