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Empirical research and application of ARIMA-GJRGARCH model on effectively creating Forward Freight Agreement trading signals

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Abstract
This study examines the volatility of the forward freight agreement (FFA) time series in the dry bulk shipping market. Series pattern analysis is first performed to determine the volatility and the characteristics of the unique FFA price time series. It then applies the ARIMA-GJRGARCH model to the Capesize FFA time charter (C5TC) and specific voyage charter one-month contracts (C3, C5 and C7), creating long or short signals, which helps market participants with FFA trading or hedging. In this study, these signals are collected and used to calculate the profit and loss for a specific period. Finally, the model-based return results are compared with the common buy-and-hold strategy. The empirical result suggests that this methodology is effective in generating trading signals, especially in the volatile periods, providing traders with prompt warnings about imminent market shocks. The purpose of the study is to examine whether this volatility-focused method is efficient in modelling FFA time series, and it also provides a handy method that may help market players make more accurate predictions when volatile days arrive.

Introduction

When used for hedging freight risk and making speculative profit through price spread, the forward freight agreement (FFA) has been a popular tool for shipowners, charterers and other participants. This over-the-counter derivative can be traded either in a forward contract or option, cleared by Baltic Exchange appointed partners that provide assurance and safety for both parties. In the past decades, some researchers thought that FFA helped transmit the future market outlook to the current market, reflecting well the fundamental basics of supply and demand. On the other hand, some argued that the involvement of speculators without any assets exacerbated the volatility of the freight market.

Kavussanos, Visvikis and Batchelor (Kavussanos, Visvikis & Batchelor, 2004) tried to identify the influence of FFA on the fluctuation of the physical market, and they found that it did reduce the volatile situation and noted the asymmetric effect on some specific shipping routes. They also used the controlled factors to measure the extent of the volatile impact, and the results showed that not all routes were improved by forward trading. Therefore, FFA might not have a substantial influence on the physical market, but it did enhance the transmission of market outlook in terms of speed and accuracy. Additionally, this situation can also be observed in the second-hand ship market. Alizadeh et al. (Alizadeh, Thanopoulou & Yip, 2017) used a heterogeneous agent model to quantify the collective behavior of speculators and operators, and they found that the short-term trading strategy based on the former group had better performance than the latter investors, who tend to hedge for their specific assets.

Regarding information transfer, the new information always exerted influence on bulk commodities derivative prices before it extended to the freight forward market, according to the spill-over research conducted by Kavussanos et al. (Kavussanos, Visvikis & Dimitrakopoulos, 2014). Chen et al. (Chen, Meersman & Voorde, 2010) also analyzed the spill-over effect between Capesize and Panamax based on volatility, and the results showed that the interaction between them changed all the time. Tsouknidis (Tsouknidis, 2016) applied the multivariate DCC-GARCH model to dry and wet freight rates and found, across shipping markets, there was a significant volatility spill-over effect that changed over time. Chen and Wang (Chen & Wang, 2004) analyzed the asymmetric existence with the EGARCH model in the dry bulk market, and they found that the freight slump period showed more of a leveraging effect than the rally period and all the relationships were negative. Among which, the contracts with bigger deadweight tend to exert more substantial leveraging influence than the smaller vessels. FFA contracts are always considered as indicators that can predict future physical prices. However, Kassimati and Veraros (Kassimati & Veraros, 2017) found that, although FFA was good at pointing at the changing price direction, the predictive capability is only just better than simple models and only expiring contracts underlying small vessels were closer to the actual future prices.

Kavussanos (Kavussanos, 1996) assessed the volatility of the dry bulk market and found the time charter rates tended to fluctuate far more than the voyage freight; meanwhile, the bigger vessels bore more risk than the smaller ones. Although today's price level is much different from the late 1990s, it is worth noting that the shipping structure remains the same. Since the bigger bulkers are used specially to carry iron ore or coal for specific routes and their size are easily restricted by the port infrastructure and berth draft. In comparison, the smaller bulkers are much more flexible in choosing the cargoes to carry and the destinations for them to go. Therefore, for the bigger bulkers, these limitations contribute more risk in their operating and financial environments. Xu et al. (Xu, Yip & Marlow, 2011) measured the dynamic relationship between freight volatility and the general vessels' size change using the AR-GARCH model and GMM regression. The results showed that the ship size did pose a positive effect on the freight rate fluctuation; meanwhile, the bigger vessels reacted more strongly than the others. Papailias et al. (Papailias, Thomakos & Liu, 2017) assessed the cyclical characteristics of the BDI and its effect on prediction efficiency. They found that there was a persistent cyclical pattern, which lasted for three and five years.

Batchelor et al. (Batchelor, Alizadeh & Visvikis, 2007) applied the VECM model to major shipping FFA contracts and found that the forward did help predict the spot rate. However, the VECM was not that useful in predicting the forward price, while the ARIMA and VAR models showed a greater fitting efficiency. Roar, Georg and Ole (Roar, Georg, & Ole, 2020) analyzed whether the composition of the current Baltic Supramax Index has impact on the FFA hedging performance. To do this study, they applied a bootstrap method and a confidence interval, calculating the hedging ratios for a specific situation. Their findings suggest that the change in the index hardly influence the hedging efficiency. Konstantinos and Nektarios (Konstantinos & Nektarios, 2021) investigated the inherent relationship between the prices of commodity and the bulker freight rates using a threshold regression approach. The results suggested there exists a positive relationship between time charter rates of different bulkers and their relevant commodities' prices. However, not all the carried cargo prices show significance on the charter rates. Xu et al. (Xu et al., 2021) used a rescaled ranged analysis (R/S) to analyze the memory effect of the dry Panamax and Handysize markets. The results showed that the index series of these two markets have a long memory with 426 days for Panamax and 206 days for Handysize. This finding provided the maritime participants with a handy tool to identify the shipping cycles of different dry bulk submarkets.

Although the previous research results showed the inherent characteristics of the current dry bulk market, little has been done on the model performance assessment of the real FFA market. In other words, the shipping participants need to find a handy and reliable method to improve the forecast accuracy and to better manage their risk. This study aims to apply the conditional variance dealing model to the dry bulk FFA time series and measure its asymmetric effects. The GJRGARCH model is an excellent choice to separately assess the downward risk in the estimation process and create the forecasting signals. The paper is organized as follows. After the

Methodology briefly introduces the methodology used in this analysis, the following Section presents the descriptive summary of the input data and the unique characteristic of the real FFA market. The next Section provides the one-period individual estimation for each FFA contract and gives the final trading performance through using this model. The last Section compared the results with a buy-and-hold strategy and summarizes the conclusion.

Methodology

The GJRGARCH variance model

Based on the traditional GARCH model, Glosten, Jagannathan and Runkle (Glosten, Jagannathan & Runkle, 1993) introduced the adjusted model that considers leverage effects and differentiates the impact of positive and negative prediction error separately. To give it economic sense, the greater variance is more likely to be observed after a large negative return rather than after a large positive return. Therefore, the GJRGARCH model is composed of two equations: the first formula measures the variances when the negative case happens, while the other one observes the variances when the positive events occur, so that:

$$\sigma_t^2 = \begin{cases} (\alpha+\gamma)\, e_{t-1}^2 + \beta\, \sigma_{t-1}^2 + \omega, & e_{t-1} \le 0 \\ \alpha\, e_{t-1}^2 + \beta\, \sigma_{t-1}^2 + \omega, & e_{t-1} \ge 0 \\ e_t \sim N\left(0, \sigma_t^2\right) \end{cases} \tag{1}$$

It is worth noting that, under the negative scenario, i.e. when the e_{t-1} is less than zero, the variances should be given a larger coefficient γ to reflect its leverage effect. γ is also a vital coefficient to measure the asymmetric extent for individual FFA contracts. Under the positive scenario, the common GARCH (1,1) is always set as the equation for the GJRGARCH model. To make sure σ_t^2 is positive and realistic, α, β and γ need to be greater than zero at all times. Additionally, to ensure σ_t^2 reverts to the long-run variance, the sum of α and β should be less than one.

In the GJRGARCH model, σ^2_{t-1} is the most recent variance that could influence the current variance σ_t^2 by the coefficient β. In this article, we are analyzing the Ln return series, i.e. $R_t = \mathrm{Ln}(\mathrm{Price}_t/\mathrm{Price}_{t-1})$ rather than the price itself. In financial practice, Ln return is always interpreted as the continuously compounded return, which is a hypothetical extreme value that does not exist in the real world.

The ARIMA mean model

Therefore, the e_{t-1} is the previous difference between the actual return and the predicted return, $e_{t-1} = R_{t-1} - \mu$. For the predicted return μ, there are several alternative mean functions to choose from; the simplest method is to treat it as a constant value or take the rolling average of the historical returns. In this study, we will use the ARIMA model to measure it:

$$\begin{cases} (R_t - \mu) = \alpha_1 (R_{t-1} - \mu) + \cdots + \alpha_p \left(R_{t-p} - \mu\right) + \\ + \omega_t + \beta_1 w_{t-1} + \cdots + \beta_q w_{t-q} \\ \nabla^d R_t = \omega_t \end{cases} \tag{2}$$

Box and Jenkins (Box & Jenkins, 1970) introduced ARMA, which is composed of the AutoRegressive (AR) and MovingAverage (MA) models, in which ω_t is the white noise with zero mean and a constant variance. The ARMA model tends to simultaneously capture both the historical behaviors through AR and unexpected events or economic shocks through MA. The α_p and β_q are the coefficients of the previous return difference and shocks. ∇^d is the repeated difference operator applied to the original R_t, which aims to convert the time series from the non-stationary to the stationary pattern.

With the ARIMA model as the mean formula and GJRGARCH as the variance formula, we are able to forecast the trading signals on a rolling basis of 500 days, roughly taken as two years' trading days. But this period can be adjusted to achieve the best estimation performance. This mean-variance mixed method would quickly provide an exact forecast, thanks to the "rugarch" package (Ghalanos & Kley, 2020). Furthermore, to make it easier to compare the result with the common buy-and-hold strategy, the signs of each forecasting value are taken.

Description of the data

In this paper, ARIMA-GJRGARCH is applied to the Baltic Exchange Capesize FFA contracts daily Ln return series. Among them, only C5TC 1MON is starting from April 2014 to December 2019 since it is a new benchmark aimed at replacing the previous C4TC contract. Other contracts, i.e. C3 1MON, C5 1MON and C7 1MON, are all covering the 2010 to 2019 period, totaling 2522 observations. As stated before, the Ln return series has economic sense but does not exist in the real world. C5TC consists of the weighted time-charter average of five bulker routes

(C8_14·0.25, C9_14·0.125, C10_14·0.25, C14·0.25, C16·0.125) based on 180,000-Dwt, non-scrubber bulkers. C3 and C5 also represent the non-scrubber routes of Tubarao-Qingdao and Tubarao–Qingdao, respectively, carrying 160,000 mt or 170,000 mt iron ore. C7 stands for the Bolivar–Rotterdam route carrying 150,000 mt or 160,000 mt coal. Figure 1 shows the physical and FFA daily contract prices of C5TC, C3, C5 and C7. Figure 2 shows the daily volatility time series of these FFA contracts.

It is evident that the spot and forward price has a high correlation and, due to the existence of different market fundamentals as discussed in the introduction, the Capesize pattern is different from other sectors such as Panamax and Handysize. As for the volatility series, these daily observations in one sense are the continuous daily returns, and we can find C5TC 1MON is more volatile than other contracts. Besides this, there are many clusters that happen from time to time; therefore, the ARCH model is considered to tackle this situation. Descriptive statistics of these FFA contracts are displayed in Table 1. We can also determine from sample variance that C5TC 1MON tends to fluctuate more strongly than the others. From Jarque–Bera statistics, we have sufficient evidence to say that all these series

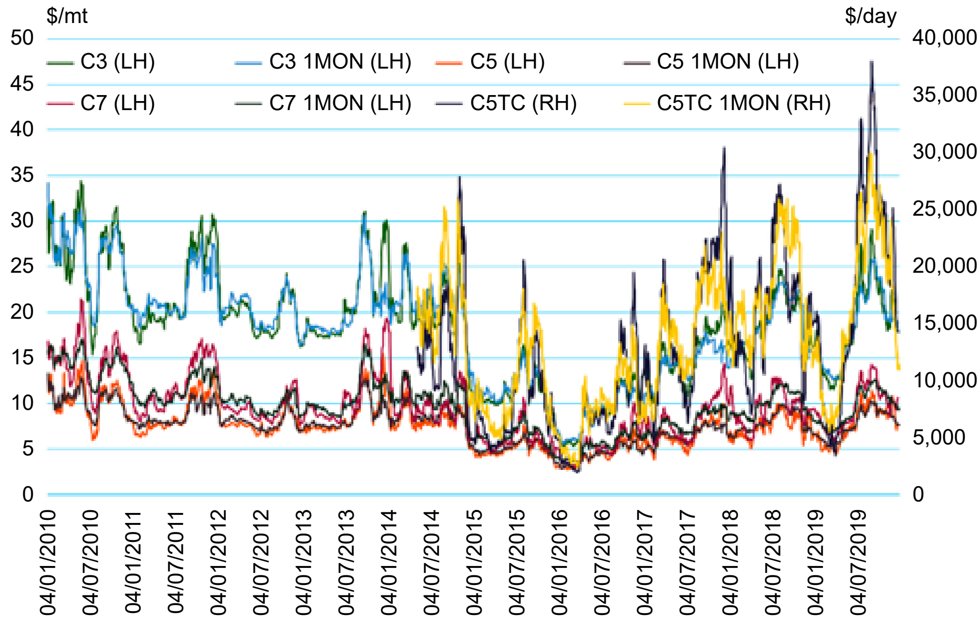

Figure 1. Spot and FFA(1MON) time series of C5TC, C3, C5 and C7

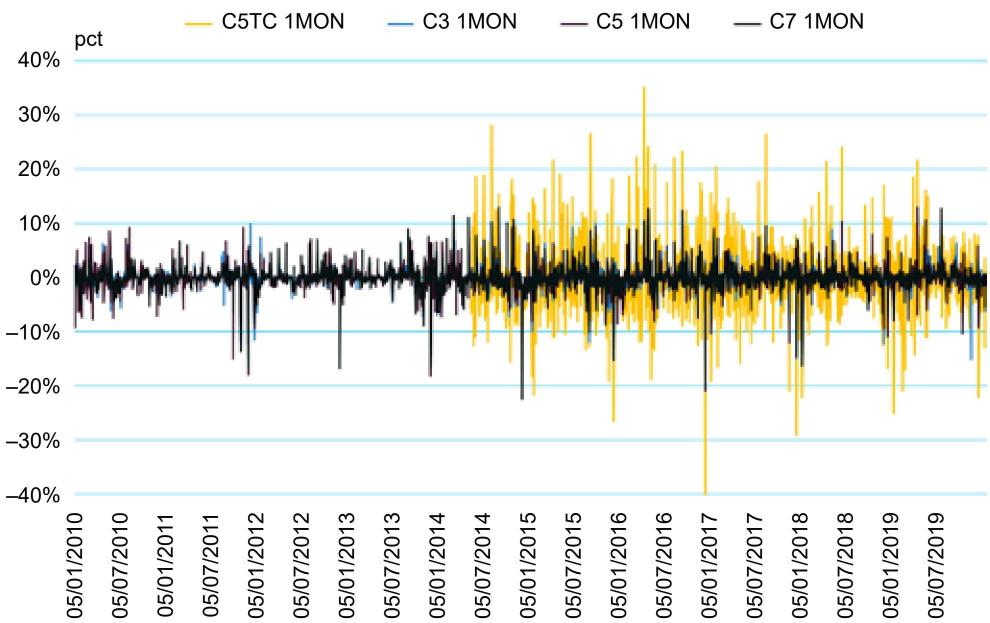

Figure 2. FFA(1MON) daily volatility of C5TC, C3, C5 and C7

Table 1. Summary statistics of spot and forward returns

	Spot				FFA			
	C5TC	C3	C5	C7	C5TC 1MON	C3 1MON	C5 1MON	C7 1MON
Count	1405	2483	2483	2483	1428	2522	2522	2522
Mean	0.00017	–0.00012	–0.00017	–0.00009	–0.00033	–0.00025	–0.00022	–0.00021
Standard Deviation	0.05619	0.02454	0.03409	0.02803	0.06622	0.01932	0.02300	0.02185
Median	–0.00457	–0.00087	–0.00143	–0.00192	–0.00364	0	0	–0.00057
Sample Variance	0.00316	0.00060	0.00116	0.00079	0.00439	0.00037	0.00053	0.00048
Kurtosis	2.81347	5.02751	3.21878	6.22271	4.84626	14.48788	10.30116	19.51419
Skewness	0.79321	0.41188	0.29589	0.47546	0.11424	–1.28477	–0.74816	–1.02138
JB Test	611	2685	1108	4100	1401	22751	11386	40455

are far from normal and, from their skewness, we are confident that they are all moderately negatively skewed, especially the FFA return series; therefore, the "skewed student distribution" setting is selected as an input in the GJRGARCH model.

Empirical performance of creating trading signals

Estimation of the ARIMA-GJRGARCH model within one period

Before we create the trading signals on the rolling basis over the whole dataset (2010–2019), we make our first attempt to estimate the ARIMA-GJRGARCH model using recent 500 daily observations from the beginning of 2018 to the end of 2019. In our study, four packages "rugarch" (Ghalanos & Kley 2020), "timeSeries" (Wuertz et al., 2020), "quantmod" (Ryan et al., 2020) and "lattice" (Sarkar et al., 2020) are needed to perform the estimation. Since the ARIMA model will be taken as the mean model in the GJRGARCH model, this is estimated first.

We select the best α_p and β_q in the function, based on information theory, as a quick tool to balance the fitness and the complexity of the model, Akaike information criterion (AIC) is used to assess the quality of the estimation. In the related expression below, k represents the number of the parameters and L maximizes the likelihood value.

$$\mathrm{AIC} = 2k - 2\ln(L) \tag{3}$$

The estimated ARIMA model, with the least AIC value, is chosen since it seeks the least number of parameters under a good fitting.

Table 2. Summary statistics of spot and forward returns

	C5TC+1MON			C3+1MON			C5+1MON			C7+1MON		
	Estimate	t value	Pr(>|t|)	Estimate	t value	Pr(>|t|)	Estimate	t value	Pr(>|t|)	Estimate	t value	Pr(>|t|)
mu	0.00	0.20	0.84	0.00	1.92	0.06	0.00	4.46	0.00	0.00	0.77	0.44
ar1	1.06	315.11	0.00	–0.46	–35.66	0.00	0.62	6806.15	0.00	–0.24	–8.24	0.00
ar2	–1.00	–166.33	0.00	1.31	86.41	0.00	–0.26	–4856.92	0.00	–0.95	–99.48	0.00
ar3				0.40	16.67	0.00	–0.63	–6938.93	0.00	0.10	3.72	0.00
ar4				–0.51	–40.97	0.00						
ma1	–1.04	–818.47	0.00	0.52	19.68	0.00	–0.61	–6426.27	0.00	0.34	61.69	0.00
ma2	1.01	5478.62	0.00	–1.25	–163.01	0.00	0.29	4705.30	0.00	1.00	1450.97	0.00
m3	0.00	25.33	0.00	–0.43	–12.64	0.00	0.60	6836.35	0.00			
ma4	0.01	155.24	0.00	0.47	74.79	0.00	0.04	1796.95	0.00			
omega	0.00	2.15	0.03	0.00	0.36	0.72	0.00	3.71	0.00	0.00	3.32	0.00
alpha1	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.60	0.55
beta1	0.90	14.02	0.00	1.00	3603.61	0.00	1.00	8542.35	0.00	1.00	38107.90	0.00
gamma1	0.15	4.38	0.00	0.00	–0.10	0.92	0.00	–0.79	0.43	–0.01	–2.18	0.03
skew	1.11	15.22	0.00	1.11	23.75	0.00	1.03	32.56	0.00	1.02	23.10	0.00
shape	5.74	4.25	0.00	2.12	543.89	0.00	2.23	64.29	0.00	2.56	60.91	0.00
Period	04/01/2018–30/12/2019			02/01/2018–24/12/2019			04/01/2018–30/12/2019			05/01/2018–31/12/2019		

The optimal order of α_p and β_q is taken as the input parameters for the next GJRGARCH estimation. Besides this, the "skewed student distribution" is also selected as the distribution model in the estimation and a further autocorrelation test is also needed to test the residuals. The standardized residual series formula is written as follows:

$$\text{standardized residuals} = = \frac{\text{actual values} - \text{estimated values}}{\text{estimated sigmas}} \tag{4}$$

In our study, the Ljung-Box test for lag 30 is conducted for each contract, which checks if there is any autocorrelation existing in the residual series. The results are given in Tables 2 and 3.

Table 3. Box-Ljung test of the residuals

	χ-squared	*df*	*p*-value
C5TC+1MON	28.051	30	0.5678
C3+1MON	36.197	30	0.2017
C5+1MON	31.406	30	0.3957
C7+1MON	37.233	30	0.1704

Due to inclusion of the ARIMA rather than a simple constant value as the mean model, we can find that the orders of AR and MA are different, and among them, the C5TC+1MON FFA contract has the minimal number for the mean model. It is obvious that all the *p* values for alpha1 are all higher than 0.05 and their *t* values are all less than 2, so we can say that these estimated parameters are not statistically different from zero. The above specific result does not matter since the aim of this paper is to apply the model to every 500 rolling observations through all their history. The Ljung-Box test shows all the *p* values are higher than 0.05 under a χ^2 distribution, which is a strong piece of evidence suggesting that we cannot reject the null hypothesis, indicating that the residual series is more like white noise. Therefore, ARIMA-GJRGARCH is a fair model fitting for the C5TC+1MON daily return series; the majority of parameters estimated here are statistically significant.

Creation of forecasting value & trading signals through ARIMA-GJRGARCH model

As mentioned before, the ARIMA-GJRGARCH estimation model is applied to all period from Jan 2010 to December 2019 with a rolling basis of 500 days, i.e. two years. Each estimation produces one-day forecasting returns right after the 500 days input. In our study, since we deal with the Ln Return series instead of the price directly, the forecasting returns are converted back into the price series for display purposes. Figure 3 shows the actual and predicted one-day ahead FFA value.

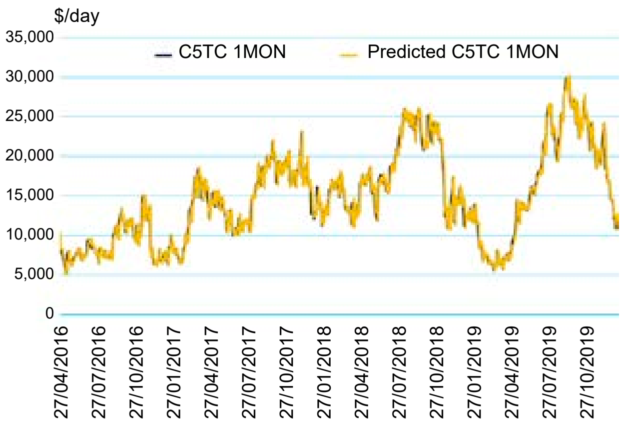

Figure 3. C5TC 1MON and predicted C5TC 1MON

For sake of simplicity, the signs of all the one-day forecasting returns are taken and multiplied with the actual daily return for that day. Figures 4–7 vividly show a scenario that if we invested $1 at the beginning of the timeline and traded C5TC 1MON, C3 1MON, C5 1MON and C7 1MON FFA contracts every day using the ARIMA-GJRGARCH model, the equity would become $8.05, $331.86, $100.44, $989.74 respectively on 31st Dec 2019, equivalent to 70%, 106%, 77% and 136% average compounded annual return since the start of the trading; otherwise, we would receive only $1.11, $0.67, $0.71 and $0.68 with the buy-and-hold method.

It is obvious that the ARIMA-GJRGARCH model has a good performance for all the contracts, especially on the C3 and C7 FFA contracts, while the buy-and-hold method can only keep a constant 1%–2% annual growth rate (Table 4). However, we still find several large malfunctions in the C5TC

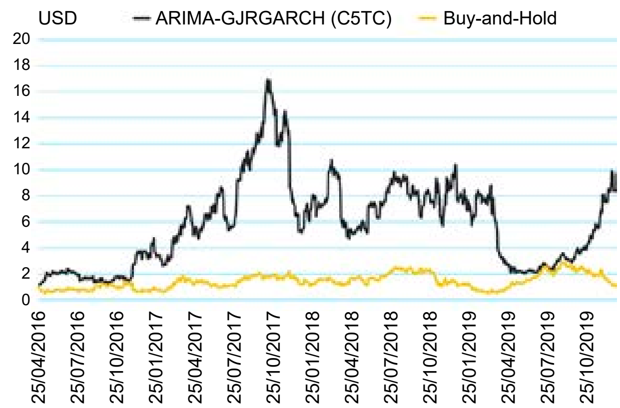

Figure 4. Scenario of investing $1 at the launch of FFA C5TC+1MON

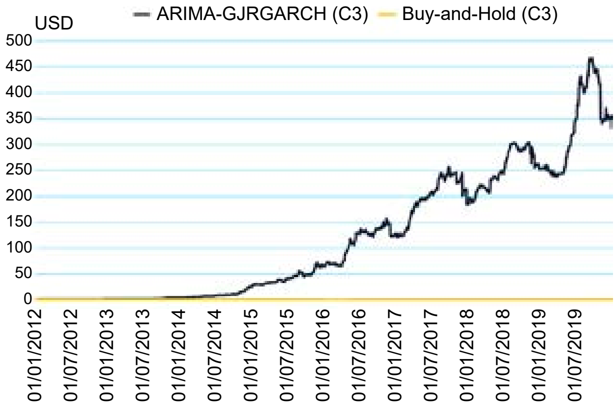

Figure 5. Scenario of investing $1 at the launch of FFA C3+1MON

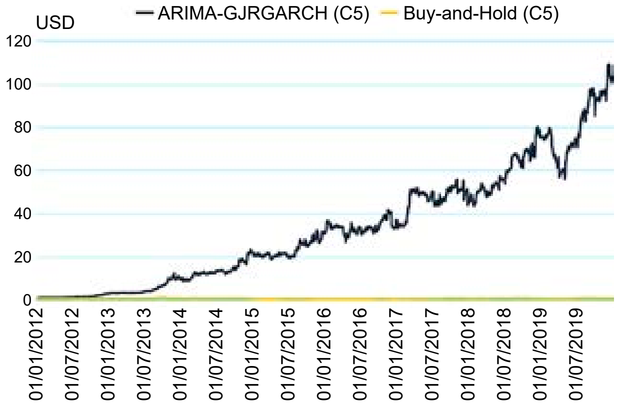

Figure 6. Scenario of investing $1 at the launch of FFA C5+1MON

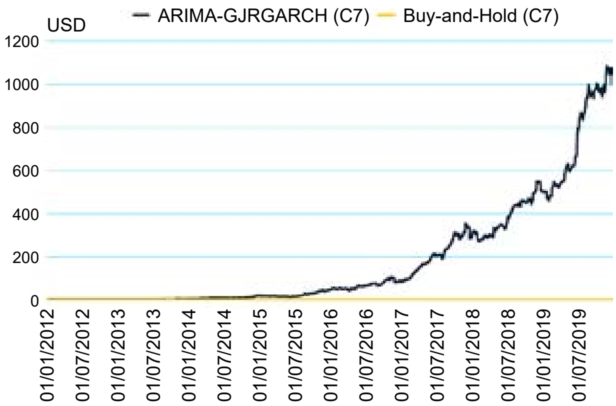

Figure 7. Scenario of investing $1 at the launch of FFA C7+1MON

1MON FFA contract, due to substantial volatility that is unable to be correctly detected by the model, which results in large amounts of loss. Specifically, this time charter contract is a weighted average of four individual routes; therefore, it is full of various risks and thus, besides the econometric forecasting tool, the fundamental analysis is necessary for decision making in practice.

Conclusions

From the above results, it is easy to point out that this volatility-focused method is generally efficient in modelling FFA time series, especially for voyage contracts due to their fixed routes and the similarity in carried cargo. All the model-based trading methods, only based on the predicted signals, perform much better than the simple buy-and-hold method. However, as for the C5TC FFA contract, since it is composed of different seaborne routes and arbitrary weightings, the forecast accuracy hardly reaches the same performance as the voyage FFA contracts. Therefore, in a future study, the breakdown of the C5TC FFA contract and an optimization of the weightings, could produce a better solution that improves the predictions. Moreover, the model-based method creates more accurate values during the volatile periods. This study is an empirical analysis of the FFA trading strategy, and the ARIMA-GJRGARCH model used for Capesize contracts can be applied to other Baltic Exchange FFA contracts as well when a due diligence is performed.

There are remains some limitations in this model. It is worth noting overall that, although the performance of this strategy is much better than the buy-and-hold method, the short-term FFA trading may still need to account for extra econometric and technical methods. From the perspective of a real trading environment, we assume that the Capesize FFA market is liquid and convenient to a similar extent to other future and option trading, which can open and close positions very quickly. However, due to the traditional structure and trading practices of the forward agreement, the FFA contract is always open

Table 4. Compound annual (CAGR) and average annual growth rate (AAGR)

		C5TC+1MON	C3+1MON	C5+1MON	C7+1MON
ARIMA-GJRGARCH Model	CAGR	70.28%	105.96%	77.32%	136.04%
	AAGR	95.64%	138.32%	96.49%	152.28%
Buy-and-Hold Method	CAGR	N/A	N/A	N/A	N/A
	AAGR	2.27%	2.47%	1.40%	1.09%

and settled outside the exchange, which may take more time and incur extra service fees that cannot be determined accurately. The implication of this research is critical for maritime participants and financial institutions, it will provide another useful tool for their prediction and risk management tasks.

References

1. Alizadeh, A., Thanopoulou, H. & Yip, T.L. (2017) Investors' behavior and dynamics of ship prices: A heterogeneous agent model. *Transportation Research Part E: Logistics and Transportation Review* 106(10), pp. 98–114, doi: 10.1016/j.tre.2017.07.012.
2. Batchelor, R., Alizadeh, A. & Visvikis, I. (2007) Forecasting spot and forward prices in the international freight market. *International Journal of Forecasting* 23(1), pp. 101–114, doi: 10.1016/j.ijforecast.2006.07.004.
3. Box, G.E.P. & Jenkins, G. (1970) *Time series analysis, forecasting and control*. San Francisco: Holden-Day.
4. Chen, S., Meersman, H. & Voorde, E.V.D. (2010) Dynamic interrelationships in returns and volatilities between Capesize and Panamax markets. *Maritime Economics & Logistics* 12(1), pp. 65–90, doi: 10.1057/mel.2009.19.
5. Chen, Y.-S. & Wang, S.-T. (2004) The empirical evidence of the leverage effect on volatility in international bulk shipping market. *Maritime Policy & Management* 31(2), pp. 109–124, doi: 10.1080/0308883042000208301.
6. Ghalanos, A. & Kley, T. (2020) rugarch: Univariate GARCH Models. R package version 1.4-4.
7. Glosten, L.R., Jagannathan, R. & Runkle, D.E. (1993) On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance* 48(5), pp. 1779–1801, doi: 10.1111/j.1540-6261.1993.tb05128.x.
8. Kasimati, E. & Veraros, N. (2017) Accuracy of forward freight agreements in forecasting future freight rates. *Applied Economics* 50(7), pp. 743–756, doi: 10.1080/00036846.2017.1340573.
9. Kavussanos, M.G. (1996) Comparisons of volatility in the dry-cargo ship sector. Spot versus time-charters, and smaller versus larger vessels. *Journal of Transport Economics and Policy* 30(1), pp. 67–82.
10. Kavussanos, M.G., Visvikis, I.D. & Batchelor, R.A. (2004) Over-the-counter forward contracts and spot price volatility in shipping. *Transportation Research. Part E: Logistics and Transportation Review* 40(4), pp. 273−296, doi: 10.1016/j.tre.2003.08.007.
11. Kavussanos, M.G., Visvikis, I.D. & Dimitrakopoulos, D.N. (2014) Economic spillovers between related derivatives markets: The case of commodity and freight markets. *Transportation Research Part E: Logistics and Transportation Review* 68, pp. 79–102, doi: 10.1016/j.tre.2014.05.003.
12. Konstantinos, D.M. & Nektarios, A.M. (2021) The relationship between commodity prices and freight rates in the dry bulk shipping segment: A threshold regression approach. *Maritime Transport Research* 2(1), 100025, doi: 10.1016/j.martra.2021.100025.
13. Papailias, F., Thomakos, D.D. & Liu, J. (2017) The Baltic Dry Index: cyclicalities, forecasting and hedging strategies. *Empirical Economics* 52, pp. 255–282, doi: 10.1007/s00181-016-1081-9.
14. Roar, A., Georg, M.S.A. & Ole, M.H. (2020) Baltic Exchange index changes and FFA hedging efficiency. *Transportation Research Procedia* 48(8), pp. 107–122, doi: 10.1016/j.trpro.2020.08.010.
15. Ryan, J.A., Ulrich, J.M., Thielen, W., Teetor, P. & Bronder, S. (2020) quantmod: Quantitative Financial Modelling Framework. R package version 0.4.17.
16. Sarkar, D., Andrews, F., Wright, K., Klepeis, N. & Murrell, P. (2020) lattice: Trellis Graphics for R. R package version 0.20-41.
17. Tsouknidis, D.A. (2016) Dynamic volatility spillovers across shipping freight markets. *Transportation Research Part E: Logistics and Transportation Review* 91(7), pp. 90–111, doi: 10.1016/j.tre.2016.04.001.
18. Wuertz, D., Setz, T., Chalabi, Y. & Maechler, M. (2020) timeSeries: Financial Time Series Objects (Rmetrics). R package version 3062.100.
19. Xu, H., Tao, B., Shu, Y. & Wang, Y. (2021) Long-term memory law and empirical research on dry bulks shipping market fluctuations. *Ocean & Coastal Management* 213, 105838, doi: 10.1016/j.ocecoaman.2021.105838.
20. Xu, J.J., Yip, T.L. & Marlow, P.B. (2011) The dynamics between freight volatility and fleet size growth in dry bulk shipping markets. *Transportation Research Part E: Logistics and Transportation Review* 47(6), pp. 983–991, doi: 10.1016/j.tre.2011.05.008.

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