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Modelling Volatility and Leverage Effect in Container Freight Market

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Abstract

Shipping is highly volatile, cyclical, and capital-intensive industry based on the prevailing price levels, which makes ship-owners or companies to take an account of market volatility to run stable business operations. Thus, knowing volatility structure would put them in healthy decision-making process of portfolio diversifications, hedging and managing freight rate risks and forecasting shipping freights rates. Therefore, modelling the volatility of container freight market provides an effective prediction mechanism, which can enhance the decision-making process among shipping players. The purpose of this study is to examine the properties of volatility in the industry standard Shanghai Containerized Freight Index (SCFI) return values by employing an Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model. The results of empirical analysis indicate that both volatility persistence and leverage effect are obvious for SCFI, meaning the impact of external shocks in container shipping market are asymmetric. Also, container freight rates require a long time for the effects of the shocks to be disperse on their own. Lastly the results revealed high index sensitivity ratios for the model, which supports the phenomenon of shipping industry being one of the quickest and harshest reflecting sectors to the developments in the global economy.

Keywords: Container Shipping, Freight Market, Leverage Effect, Volatility

JEL Classification: C58, F00, N70, R49

1. Introduction

The Shanghai Containerized Freight Index (SCFI) has been developed by the Shanghai Shipping Exchange (SSE) to reflect the current situation and overall

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fluctuations of international container shipping market. SCFI is regarded highly as leading indicator for container shipping as well as international trade. SSE publishes composite SCFI and its sub-indices on weekly basis. Due to the recent developments in the impacting factors such as world economy, politics, and supply-demand relationships the container freight index experienced violent fluctuations. This situation brings certain difficulties for stakeholders in container shipping market to make sound decisions. Therefore, understanding the characteristics of volatility has an utmost importance to avoid crucial risks both theoretically and practically.

One of the most important factors for volatility to understand is the leverage effect phenomenon in this matter. The leverage effect or the asymmetric volatility is simply described as the negative relationship between asset value and volatility (Black, 1976). To study the properties of volatility, Mandelbrot (1963) focused on the volatility clustering and found that high positive returns are followed by high negative returns, and low positive returns are followed by low negative returns. This set the basis for many studies conducted upon volatility and led to the proposition of Autoregressive Conditional Heteroscedasticity (ARCH) models. By pointing out that the residuals of the time series are not homoscedastic in most cases, Engle (1982) pointed out that in those cases the estimations can be made with the ARCH model. With more and more attention drown upon the subject, many improvements and extensions are made to ARCH model to remove many of the constraints and offer different aspects leading to improved estimation performance and asymmetric effect consideration. One such improvement made by Bollerslev (1986) to remove the constraint of unconditional variance having to be constant in ARCH models to create Generalized Conditional Heteroscedasticity (GARCH) model. After that Nelson (1991) proposed EGARCH model, which considers the signs of the lagged error terms of the conditional variance to account for the volatility asymmetry. To summarize, the EGARCH model has several advantages over the traditional GARCH model. The most important one is its logarithmic specification, which allows for relaxation of the positive constraints among the parameters. Another advantage of the EGARCH model is that it incorporates the asymmetries in volatilities to answer whether good news or bad news generate more volatility. Another advantage of the EGARCH model is that it successfully captures the persistence of volatility shocks. Based on these advantages, we applied the EGARCH model for modelling the volatility and analysis of leverage effect of the container freight market. Other than contributing to the literature by employing a more advanced model in the analysis of freight market volatility, this study includes the Corona Virus Disease 2019 (COVID-19) period, which came as a highly disruptive event for global economy and shipping, in analysis of explaining the volatility structure of container freight market.

The rest of the study is organized as follows. The second part explores theoretical backgrounds of company reputation literature. The third part shows the methodology and data collection, and the fourth part presents the results, while the last part concludes the study with directions for future research.

2. Shipping Market Volatility

During the last decade, the rapid economic growth of emerging countries has led to substantial volatility for all sub-sectors of shipping freight markets. Kavussanos and Visvikis (2006) discussed shipping freight rates and pointed out that enormous freight volatility and a great level of risk characterize the shipping market. Adland and Cullinane (2006) pointed out that short-run changes in freight rates might easily create bubbles and crashes. Because the freight rate volatility is the most important aspect of maritime business profitability, and during the times of turmoil it can threaten business survival. Therefore, it is crucial for all the stakeholders in maritime business to grasp the return lead–lag relationship and volatility structure of shipping markets.

Regarding the possible sources of freight rate volatility, it is important to keep in mind that costs which generate the freight rate as a result are highly volatile and can swing drastically in short periods (Stopford, 2009). For example, Lee and Ryu (2019) investigated the factors that contribute to freight market volatility in the US spot market. The authors analyzed the relationship between spot rates, fuel prices, and other macroeconomic indicators such as gross domestic product, industrial production, and employment. They suggest that fuel prices and macroeconomic conditions have a significant impact on freight market volatility.

Kavussanos (1996a) pointed out the necessity of employing Autoregressive Conditional Heteroscedasticity (ARCH) type modelling when assessing risks in spot and time charter dry bulk markets, as their variances are not constant over time. Kavussanos (1996b) then examined the volatility in the world tanker market for secondhand vessels via ARCH modelling. He found that larger segments of tanker prices such as VLCC fluctuate wilder than smaller segments and suggested that risks in the tanker industry have decreased since the first part of the 1980s. Kavussanos (1997) then proceeds to examine the volatility properties of secondhand market for different size dry bulk vessels with ARCH type modelling. The study reveals volatility clustering for all segments and higher volatility for larger size ship prices. With the shipping freight markets are highly volatile and cyclical, companies are constantly searching for ways to evaluate the changes in freight rates and reducing the business risk and uncertainties. This study aims to contribute to the literature by considering development of a container shipping volatility assessment method using the historical SCFI data. This method could be an utmost importance for interested parties. In this paper, the concept of Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model is proposed for the modelling the volatility of SCFI. With it, the volatility properties and risk structure for SCFI are thoroughly investigated.

3. Methodology

This study employs a financial time series analysis as the main research methodology. After conducting research upon the changing and asymmetric volatility models to decide on which time series approach to be taken, an EGARCH model was constructed to model the volatility and understand its properties in SCFI.

Data

The data used on analysis consists of weekly SCFI data published by the Shanghai Shipping Exchange between 16 October 2009 – 27 May 2022. The index consists of 634 observations, which is a considerable number to capture the changes in asymmetric volatility over time and volatility clustering. The index data were gathered from Bloomberg Professional to prevent the mismatch and missing value problems that may occur from gathering data from different databases which do not perfectly correspond with each other. Figure 1 provides the line graph of raw SCFI data to provide an understanding of the trend in the container freight rates. Also, the descriptive statistics of raw series are given below in Table 1.

When Table 1 is inspected the high range between maximum and minimum index values and the enormity of the standard deviation of the index are first to be noticed. Also, when the skewness, kurtosis, and Jarque-Bera test statistics are inspected it can be said that the index is fat-tailed, skewed to the right and does not exhibit a normal distribution (Jarque and Bera, 1980).

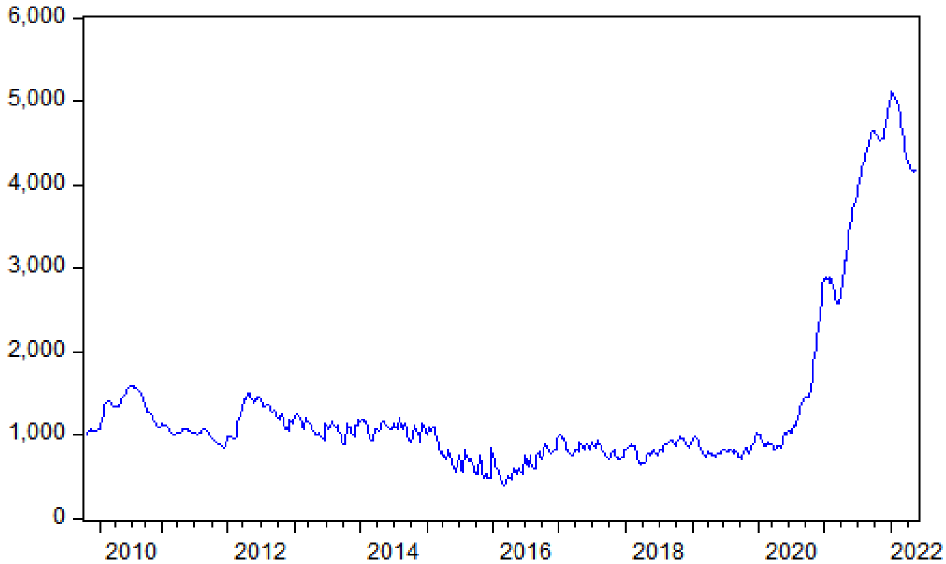
Table 1. Descriptive Statistics of SCFI

	SCFI
Mean	1331.517
Median	1009.390
Maximum	5109.600
Minimum	400.430
Std. Dev.	1031.311
Skewness	2.404949
Kurtosis	7.715684
Jarque-Bera	1198.598
Probability	0.000000
Observations	634

Source: Data taken from Bloomberg Professional, Processed by Author

When Figure 1 is inspected closely, one can argue that volatility clustering and cyclical patterns are visually obvious for SCFI. Also, the start of exponential increase of the freight rates after 2020 is a clear indicator of the supply chain crisis faced during the COVID-19 pandemic period. Supply chain problems were prominent during the COVID-19 lockdown amid a variety of causes, including shifts in demand, labor shortages and structural factors. The Russia-Ukraine conflict and COVID-19 lockdowns in China have recently exacerbated issues, affecting supply in certain sectors including consumer goods, metals, food, chemicals and commodities.

Figure 1. Index Values of SCFI



Source: Data taken from Bloomberg Professional, Processed by Author

Preparation of the Data

Firstly, the index values must be converted into logarithmic returns to be applied in the financial time series analysis especially for EGARCH model and improve the estimation performance. The raw data converted into return series by applying the equation below to raw SCFI index values.

$$R_t = log\left(\frac{P_t}{P_{t-1}}\right)*100 \qquad (1)$$

Which P_t is the freight index value and R_t is the freight index rate of return value. After the conversion of SCFI to return series, time trend graphs were given for the visual inspection at the Figure 2 below.

When Table 2 is inspected the high range between maximum and minimum index return values and the enormity of the maximum of 53.8% weekly increase, most likely during COVID-19 period, are first to be noticed. Also, when the skewness, kurtosis, and Jarque-Bera test statistics are inspected it can be said that the index returns have excess kurtosis, fat-tailed, skewed to the right and do not exhibit a normal distribution (Jarque and Bera, 1980).

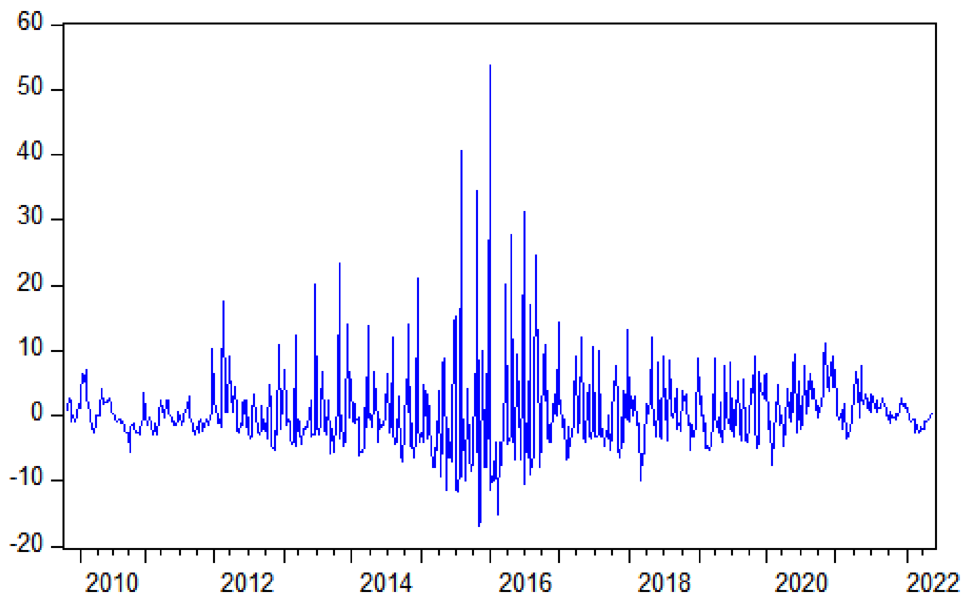
Table 2. Descriptive Statistics of SCFI Index Return Values

	R(SCFI)
Mean	0.225782
Median	-0.555901
Maximum	53.80684
Minimum	-16.81770
Std. Dev.	5.977902
Skewness	2.768789
Kurtosis	20.02891
Jarque-Bera	8453.605
Probability	0.000000
Observations	633

Source: Data taken from Bloomberg Professional, Processed by Author

When the SCFI rate of return graph at Figure 2 is examined, we can make preliminary calls that the return series of SCFI is stationary and constantly waving by the zero mean. Also, the volatility clustering is visually obvious. Although line graphs give first glance information and some insights regarding the stationarity of the series, it is a must to conduct unit root tests for ensuring the series stationarity.

Figure 2. SCFI Index Return Values



Source: Processed by Author

For ensuring the stationarity of the series, Augmented Dickey-Fuller (ADF) unit root test (Said and Dickey, 1984) and KPSS unit root test (Kwiatkowski et al,

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1992) are applied for the return series and the results of the unit root tests with intercept are given in the Table 3 and Table 4 below.

Table 3. ADF Unit Root Test

	R(SCFI)
ADF Test Statistic	-6.231125***
1% level critical value	-3.440651
5% level critical value	-2.865976
10% level critical value	-2.569191

Note: *** refers to rejection of the null hypothesis for non-stationarity at 1%.

Source: Authors' Calculations

Table 4. KPSS Unit Root Test

	R(SCFI)
KPSS Test Statistic	0.347171**
1% level critical value	0.739000
5% level critical value	0.463000
10% level critical value	0.347000

Note: ** refers to the null hypothesis for stationarity cannot be rejected at 5%.

Source: Authors' Calculations

According to the ADF test results given in Table 3 the null hypothesis, existence of unit root, is rejected at 1% significance level and therefore it can be said that the return series of SCFI do not possess unit root and it is mean stationary. As for the KPSS test results at Table 4 the null hypothesis, trend stationarity of series, cannot be rejected and 5% significance level and therefore it can be said that the return series of SCFI do not possess unit root and it is trend stationary. After evaluating the results of the ADF and KPSS tests, which complement each other, it is safe to state that return of SCFI series is stationary.

Modelling and Estimation

To produce a useful model, several steps have been followed in the scope of this study. First, the weekly series of SCFI was converted into their index rate of return form to start the modelling procedure. After that unit root tests were conducted to ensure stationarity of all index rate of return series. For the model selection process, after the quick glance of the correlograms of the series it was obvious that the series must be modelled with AR and MA components. The AR and MA orders for the models were determined using an automated search over all possible models considering up to 4 orders for both AR and MA components with an automated search with the framework outlined by Hyndman and Khandakar (2008). The search is set to minimization of Schwarz Information Criterion (SIC) amongst all possible combinations (Schwarz, 1973). Results of the ARMA parameter selection model is given at Table 5.

Table 5. SCFI Returns ARMA (4,4) Estimation Results

Variable	Coefficient	P-value	Variable	Coefficient	P-value
C	0.225205	0.9184	MA(1)	1.696424***	0.0000
AR(1)	-1.601637***	0.0000	MA(2)	1.909095***	0.0000
AR(2)	-1.737614***	0.0000	MA(3)	1.489189***	0.0000
AR(3)	-1.479992***	0.0000	MA(4)	0.835218***	0.0000
AR(4)	-0.865709***	0.0000	SIGMASQ	30.51929***	0.0000
Summary Statistics					
Log-Likelihood					-1980.957
SIC					6.3608
R^2					0.1446
ARCH-LM Test					0.2492 [0.6179]

Note: *** refers to significance at 1%.

Source: Authors' Calculations

As for AR and MA orders, the search has given the order of AR (4) and the order of MA (4) for Return values of SCFI resulting in an ARMA (4,4) structure, all parameters being significant.

After the ARMA(p,q) structure of the series is determined, an Ordinary Least Squares (OLS) model for SCFI is constructed with the determined parameters. Then the OLS model is tested against the heteroskedasticity with Autoregressive Conditional Heteroscedasticity-Lagrange Multiplier (ARCH-LM) test and the results are given at the Table 6 below.

Table 6. ARCH Test Results for SCFI Returns ARMA(4,4) Model

		RSCFI ARMA(4,4)
ARCH-LM Test	F-Statistic	6.056042
	Prob.	0.0141**

Note: ** refers to rejection of the null hypothesis for homoskedasticity at 5% significance.

Source: Authors' Calculations

ARCH-LM test checks for the existence of heteroscedasticity by regressing squared residuals of the model on lagged values of the squared residuals and a constant (Engle, 1982). With the H_0 null hypothesis representing homoscedasticity,

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the OLS model was tested. When looked at the results, the ARMA(4,4) model reject the homoscedasticity assumption of the test. Therefore, it is safe to say that the model possesses strong heteroskedastic structure, which is applicable for EGARCH type modelling.

In this study EGARCH (1,1,1) model for RSCFI series was employed. The general equation proposed by Nelson (1991) is in the form:

$$ln(\sigma_t^2) = \omega + \beta\, ln(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \tag{2}$$

Where parameter ω is variance intercept of the model, parameter β is the measurement of volatility persistence which also known as the GARCH effect, parameter α is the return coefficient of the model, which is also known as the ARCH effect, and the parameter γ is the magnitude of model's asymmetric volatility, which also known as the leverage effect parameter.

4. Findings and Discussion

The modelling procedure mentioned in the previous section has resulted in a EGARCH (1,1,1) ARMA (4,4) model for Return values of SCFI. Estimation results are presented in Table 7.

Table 7. RSCFI EGARCH (1,1,1) ARMA (4,4) Estimation Results

Variance Equation					
Variable	**Coefficient**	**P-value**	**Variable**	**Coefficient**	**P-value**
ω	-0.095602***	0.0000	γ	-0.105957***	0.0000
α	0.151440***	0.0000	β	0.994646***	0.0000
Summary Statistics					
Log-Likelihood					-1783.545
SIC					5.8042
R^2					0.0411
ARCH-LM Test					0.2492 [0.6179]

Note: *** refers to significance at 1%.

Source: Authors' Calculations

As described before the parameter β is the measurement of volatility persistence which also known as the GARCH effect. If the β value is large, longer periods of time is required for volatility to disperse and effects of a shock to be removed. The large number also implies greater fluctuations. For the RSCFI the parameter value is 0.99, which is a very high volatility persistence level. The high value of lag coefficient means that returns of SCFI require long time frames to get rid of the effects of external shocks and fluctuate wildly during innovation periods. The results suggest that shocks in return of SCFI, only disperse 0.5%, each week on its own, meaning it takes 200 weeks (approximately 3.84 years) for a shock to completely disappear on its own. The parameter α is the return coefficient of the model, which is also known as the ARCH effect. The larger the α value becomes, the quicker it shows the movements in the markets and fluctuate longer. When the estimation results are examined, it can be said that SCFI with the coefficient of 0.15 being larger than 0.1, which means volatility of the index returns are very sensitive to happenings of the market. The significance of α parameter proves the existence of volatility clustering in container freight market. And finally, the parameter γ is the magnitude of models' asymmetric volatility, which also known as the leverage effect parameter. When γ results in zero, it means that the volatility is symmetric for the series. If the parameter results in positive or negative value and becomes significant then it means the leverage effect is undeniable for the series. The sign of the γ value determines the properties of leverage effect. If γ results in a negative value, that means negative shocks or bad news generates more volatility than positive shocks or good news. If γ results in a positive value, it can be said that positive shocks destabilize the series more than the negative shocks. According to the estimation results SCFI possesses leverage effect with a negative γ value. Which means bad news generate more volatility for container freight market than the good ones. One possible reason for that because shipping is such a capital-intensive industry. When a negative development occurs in the market stakeholders might react more harshly than they react in the positive developments. Because when considering the properties of the market a negative investment and even a false investment can lead to bankruptcy, while reacting to positive happenings of the market is usually a win more decision. Black (1976) states that bad news increase the riskiness of the firms with higher debt to equity ratios and greatly increases the return volatility of the markets those firms operate in. This statement appears to be the explanation for the negative leverage effect of the container freight market, as studies conducted by Drobetz et al (2012) over the financial structures of top 115 shipping firms and by Yeo (2016) over the financial structures of top 130 shipping firms and they pointed out an average of 1.74 debt-to-equity ratio for shipping industry.

The estimation results indicate that both volatility persistence and leverage effect are obvious for container freight index returns. According to the estimations the container freight market has negative leverage, in other words bad news generate more volatility for the SCFI than the good ones. In addition to this, it can be said that container freight market requires a long time for the effects of the shocks to be disappear on their own. The volatility generated for return of SCFI by those shocks persist through approximately 200 weeks (3.84 years). Also, SCFI has very high sensitivity ratio, which means that the index reflects quickly to the

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happenings of the shipping and economy in general. This also proves the phenomenon of shipping industry being one of the quickest and harshest reflecting sectors to the developments in the global economy. Modeling procedure based on SIC, significance of variables, and log-likelihood criteria have ended up with functional models with appealing statistical diagnostics.

5. Conclusion

This study focused on modelling the volatility of SCFI via EGARCH type model. The weekly index returns of SCFI during 16 October 2009 – 27 May 2022, consisting of 633 observations. The examined return values showed leptokurtosis and volatility clustering, both being fore signs of heteroskedasticity. For the next stage, autoregressive structures of index return series were determined by estimating with an OLS estimator. After determining the AR and MA operators for series residuals of the series were tested against heteroskedasticity via ARCH-LM test. According to the heteroskedasticity test results residuals of the index return series, which were estimated with OLS, are under considerable ARCH effect and found to be suitable for a GARCH type modelling procedure. Therefore, with the aim of the study in mind return of the SCFI series found to be most suitable for EGARCH(1,1,1)-ARMA(4,4) model, after various testing and post estimation diagnostics. This model can serve as a reliable analytical tool for decision makers in container shipping market. When looking at the estimation results as an investor's perspective the leverage effect emerges as a core function of the freight mechanism of the container market. With the high sensitivity, high shock persistence and negative leverage effect properties considered, shipping industry, which is already infamous with its very risky structure, will surely has to stay on alert for any crisis at the global economy and will be tested harshly as it has been throughout the recent history. Like any other conducted research, this study also has certain limitations. First limitation is that due to SCFI started publishing in 2009, the analysis does not consider the time before 2009. Therefore, notable events affected container freight market volatility such as financial crisis of 2008 could not be captured. The second limitation is that the analysis is conducted on a freight index rather than using actual freight rates. Although SCFI is considered as the primary indicator for container freight market, usage of actual freight rates could yield more accurate results. For the future studies, using other container freight indices on modelling container market freight rates and comparing their results with SCFI could provide useful insight on how these indices in the market differ when capturing volatility and leverage effect on container freight market.

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