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Forecasting container shipping freight rates for the Far East - Northern Europe trade lane

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Abstract

This study introduces a state-of-the-art volatility forecasting method for container shipping freight rates. Over the last decade, the container shipping industry has become very unpredictable. The demolition of the shipping conference system in 2008 for all trades calling a port in the European Union (EU) and the global financial crisis in 2009 have affected the container shipping freight market adversely towards a depressive, and non-stable market environment with heavily fluctuating freight rate movements. At the same time, the approaches of forecasting container freight rates using econometric and time series modelling have been rather limited. Therefore, in this paper, we discuss contemporary container freight rate dynamics in an attempt to forecast for the Far East to Northern Europe trade lane. Methodology-wise, we employed Autoregressive Integrated Moving Average (ARIMA) as well as the combination of ARIMA and Autoregressive Conditional Heteroscedasticity (ARCH) model, which we call ARIMARCH. We observed that our ARIMARCH model provides comparatively better results than the existing freight rate forecasting models while performing short-term forecast on a weekly level. We also observed remarkable influence of recurrent general rate increases (GRIs) on the container freight rate volatility.

Keywords: container shipping, freight rates, forecasting, ARIMA, ARCH, GRI

Introduction

Today, about 80% of the world's total trade volume is seaborne trade and while considering developing countries alone, this percentage is 90% (UNCTAD, 2015). According to recent statistics, world seaborne trade almost tripled to 9,842 Mio. t in 2014 from 3,704 Mio. t in 1980, while containerized trade increased almost 15 times to 1,631 Mio. t in 2014 from 102 Mio. t in 1980 (UNCTAD, 2015). Like other industries, the shipping industry also suffered from the global financial crisis in 2009 (Slack, 2010). Such economic cycles are not new and are inherited part of the shipping industry for hundreds of years (Stopford, 2009). But shippers and carriers being able to predict such kinds of swings and their effects on container freight rates could save lots of money just by being able to make appropriate decisions at the right time. This is especially the case, as instruments like financial hedging of freight rates in the form of forward freight agreements (FFAs, Dixon, 2010; Dupin, 2010, Kavussanus *et al*, 2015, Miller *et al*, 2015) or index-linked container contracts (ILCCs, Drewry Shipping Consultants, 2012, Miller et al, 2015) have not received wide-spread use in the container shipping industry so far (ALPHALINER, 2013b). Moreover, a more volatile, depressive, and non-stable market environment than ever before leads to rather "illogicality" of freight rate movements in the container shipping industry today as remarked by Drewry Maritime Research (2011). Compared to the year 2013, global container carriers shipped 5.63% more cargo (UNCTAD, 2015), but made 3% less revenue in 2014 (AlixPartners, 2015). This may stem from the fact that overall freight rates remained on a very low level. Therefore, forecasting container freight rates have clearly become more necessary than previous times and the impetus on accuracy of forecasts is even greater today.

As mentioned in Fan (2011), Nielsen *et al* (2014) and Fusillo (2004), container freight rates are cyclical in nature and can fluctuate largely over the course of a single week. As for strategic planning decisions weeks are fairly short time horizons, we attempt to forecast container freight rates on both weekly as well as monthly level. However, as exact figures about demand and supply in the container shipping industry are not timely available on weekly and monthly level, we investigate freight rates from 16/10/2009 till 25/12/2015 published by the Shanghai Shipping Exchange (SSE) on a weekly basis. Nielsen *et al* (2014) mentioned that time series models are superior while demand and supply are crucial to know. Therefore, methodology-wise, we employ a time series forecasting model combining Autoregressive Integrated Moving Average (ARIMA) and Autoregressive Conditional Heteroscedasticity (ARCH) model which provides fairly better forecast results compared to existing models.

The remainder of the paper is as follows: First, in Sections 2 we discuss the principal relationship between supply-demand, freight rates and indices in container shipping and present our dataset considered for further investigation. Section 3 provides a methodological overview about past forecasting approaches, followed by an outline of our forecasting method in Section 4. In Section 5, our analysis and findings are discussed. Section 6 concludes and provides suggestions for further research.

Supply, Demand, Container Freight Rates and Indices

Freights rates play a crucial role in shipping industry simply because they are considered to be an adjustment mechanism linking supply and demand in the shipping industry (Stopford, 2009). However, proper functioning of this mechanism is more and more questioned since the repeal of the EU block exemption of liner shipping conferences in 2008 with Council Regulation (EC) No 1419/2006 (Drewry Maritime Research, 2011). But recent research by Mason and Nair (2013) showed that container shipping operators deploy a plethora of supply side flexibility tactics to cope with present over-supply (as well as under demand) in the market.

According to Stopford (2009), the working mechanism of supply-demand is rather simple as carriers and shippers try to establish a freight rate through negotiation which reflects a balance of available cargoes and shipping capacity in the market. If the capacity of total available shipping capacity is more than cargoes to be shipped, the freight rate will be low (and vice versa). After negotiation, carriers and shippers adapt to it accordingly which leads to a balance between supply and demand after some adjustment process. According to Mason and Nair (2013), carrier's supply capacity can be expressed as a combination of (a) number of employed vessels, (b) total carrying capacity (in TEU) vessels and (c) the scheduled length of journey to be completed (in terms of time and/or distance). These factors can be tackled by diverse supply-side flexibility tactics which are briefly summarised in the following with a special focus laid on the major east-west trade lanes between Far East, Europe and North America.

Around 2008 and 2009, cancelling new-built contracts or postponing delivery of new-built vessels were common as a short-term reaction to the economic downturn (Hoffmann, 2010). Afterwards, carriers tend to scrap rather older, smaller vessels in exchange of larger new-built ones with higher average carrying capacity coming into service (Hoffmann, 2010; Mason and Nair, 2013; ALPHALINER, 2014). Later on, such smaller vessels were pushed to other geographical areas on north-south and south-south trade lanes whenever new-built ones came into service - a phenomenon known as the cascading effect (Cariou and Cheaitou, 2014). Other common supply-side tactics to reduce (a) and (b) were laying off vessels and skipping of already planned schedules to increase utilization of the remaining shipping fleet in service (Hofmann, 2010). The later recently became a common feature on the Far East – Northern Europe trade lane in 2015 (ALPHALINER, 2015).

Moreover, rather short term supply-side flexibility tactics aiming on (c) are slow steaming and re-routing of vessels. It has been proven, that there is a relation between freight rate and speed of vessels: at a low freight rate, vessels tend to operate in slow speed to save fuel (Drewry Maritime Research, 2011; Ferrari *et al*, 2015). Thus it takes more time for a trip which leads to a direct reduction in available fleet capacity (Stopford, 2009) and this in turn saves bunker costs being the most important cost driver when it comes on operational costs in liner shipping (Ferrari *et al*, 2015). Re-routing vessels from Europe to Asia via the "Cape of Good Hope" has been another supply-side flexibility tactic since 2008 executed by several carriers, and this is not only to avoid Suez Canal tolls but the resulting longer voyage helps to absorb excessive shipping capacities, too (Slack, 2010; Mason and Nair, 2013).

Last but not least, the recent development of carriers collaborating in diverse forms of consortia agreements on specific trade lanes or teaming up on several trade lanes in a strategic alliance (2M, Ocean Alliance and THE Alliance at the moment, e.g. Murphy, 2016) needs to be elaborated in this context, too, as they all allow to reduce shipping capacity deployed while maintaining scheduled service with high frequency to a high extent (Marlow and Nair, 2008; Mason and Nair, 2013). Indeed, the main objectives of such consortia agreements changed over time from cost and investment sharing in connection with joint marketing activities in the early days of containerisation to more operational issues of slot sharing, vessel sharing and/or joint services provision (Evangelista and Morvillo, 1999; Midoro and Pitto, 2000; Panayides and Wiedmer, 2011; Caschili *et al*, 2014). Today, virtually every container shipping company collaborates on specific trade lanes with other carriers based on some consortia agreements which sums up to a complex cooperative container network as described by Caschili *et al* (2014) and even strategic alliances are basically formed by closing a multitude of such mutual consortia agreements among its members, too. Notably, all this is fully in line with e.g. European Commission Regulation (EC) No 906/2009 (prolonged by Commission Regulation (EU) No 697/2014 until 2020) which allows joint operation of liner shipping services without fixing of prices, deliberately restricting capacity or sales as well as allocating of markets or customers if the combined market share of the consortium members in the relevant market does not exceed 30% of total volume of goods transported in freight tonnes or TEU.

Beside these supply-side flexibility tactics, other influencing factors on freight rates in the liner shipping industry mainly stem from the freight rate structure itself. Since the 1960's, after transformation from break-bulk of general cargo to almost fully containerized trade lanes, nowadays freight rates in liner shipping are usually denominated in a single price per container (base rate) for most sorts of cargo (Slack and Gouvernal, 2011). Higher efforts coming along with handling and shipping of special cargo like outsize, heavy, reefer or hazmat are remunerated in form of diverse surcharges adding to this base rate. In addition to this, special service contract rates are offered to major customers shipping large volumes (Marlow and Nair, 2008; Drewry Maritime Research, 2011). Moreover, some pricing tactics relicts from the liner conference era contributed a lot to container freight rate volatility - at least until recently. First, carriers regularly tried to increase the base rate in form of general rate increases (GRIs), which were not only rather unsuccessful over the last years but even led to a formal anti-trust proceedings by European Commission (EC) in 2013 to 2016 (ALPHALINER, 2013*c*; EC, 2016). Second, as bunker is a major external cost driver in liner shipping, bunker adjustment factors (BAFs) were set by each individual carrier after 2008 with tendency of asymmetric pass-through as before (Wang *et al*, 2011; Notteboom and Cariou, 2013) – especially on those trade lanes where no liner shipping conference agreement existed any longer (Fung, 2014). However, this surcharge practice became redundant with overall low freight rates level (Drewry Maritime Research, 2011; Slack and Gouvernal, 2011) and falling bunker prices in 2015, so that now some carriers peg it to some fuel index (e.g. Maersk) or just abandoned it in favour of including them in the base rate (e.g. MSC, see ALPHALINER, 2013*a*). Likely the same happened with peak season surcharges (PSS) within the last years as seasonal demand increases expected by carriers consistently did not occur to such an extent. In summary, this makes the structure and dynamics of container freight rates rather complex and most of these features are hardly to be expressed in explanatory variables suitable for further econometric modelling.

For a long time, the Freight Rate Indicator by Containerisation International (CI, 2009) published on a quarterly basis for the three major east-west trade lanes between Europe, North America and Far East was considered to be the leading freight rate index in the liner shipping industry. However, the panel died in 2009 in the aftermath of repealing the EU block exemption for liner shipping conferences. After that, some other indices based on fixed panel lists of carriers and/or freight forwarders and non-vessel operators reporting their freight rates on a regular basis (e.g. Karamperidis *et al*, 2013) came up like the Aggregate Price Index of the European Liner Affairs Association (ELAA, later continued by Container Trades Statistics (CTS, n.d.), the World Container Index (WCI, n.d.) and the Ningbo Containerised Freight Index (Balticexchange, n.d.) as well as a bunch of indices published by the Shanghai Shipping Exchange (SSE, n.d.) were introduced - all in line with the guidelines on the application of Art. 81 of the EC Treaty to maritime transport services (EC, 2008). Common to all these freight rate indices is that they usually derive from the aforementioned complex freight rate structures taking a standard 20’’ TEU or 40’’ FEU dry box container as the basis.

China Containerized Freight Index (CCFI) and Shanghai Containerized Freight Index (SCFI) published on a weekly basis by SSE were taken into consideration in this paper as they are one of the only freight price indices public available on a weekly basis without delay for a longer time period. At the same time, they are often used as an underlying asset for FFAs or floating element in ILCCs (Drewry Shipping Consultants 2012; Kavussanos *et al*, 2015; Miller *et al*, 2015). SCFI reflects spot rates (CIF, CY-CY including all major seaborne surcharges) of the export container market on 15 individual shipping routes ex Shanghai, denominated in $ per TEU or FEU (SSE, 2016*b*). CCFI, however, is more comprehensive than SCFI as it reflects the overall freight level (including spot and long-term rates) of China’s export container market from 10 Chinese hub ports (Dalian, Tianjin, Qingdao, Shanghai, Nanjing, Ningbo, Xiamen, Fuzhou, Shenzhen and Guangzhou) on 14 individual shipping routes, with 1,000 points equivalent to the freight rate of a TEU or FEU at 01/01/1998 (SSE, 2016*a*).

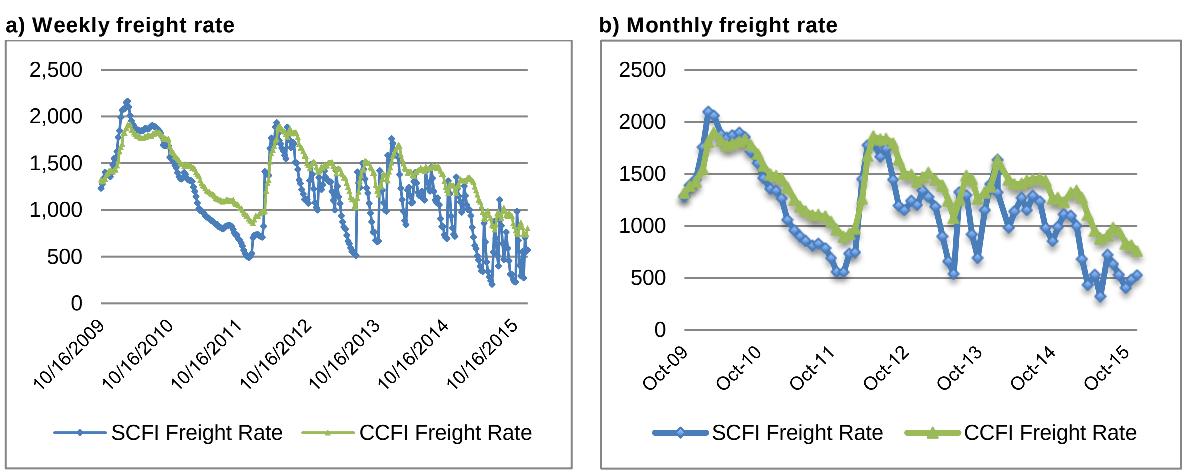


Figure 1: SCFI and CCFI Freight Rate Data

In this paper, we focus on the China to Northern Europe trade lane as this comes along with the highest volume (UNCTAD, 2015) and shows at the same time much more volatile freight rates in comparison to other routes reported in SSE. Weekly data in our dataset consists of 324 weeks of observation starting from 16/10/2009 till 25/12/2015 and monthly data consists of 75 monthly averages starting from October 2009 till December 2015. In Figure 1, SCFI and CCFI from Shanghai or Chinese hub ports to Northern Europe are depicted on a weekly and monthly level with a more detailed descriptive statistics of the dataset presented in Table 1.

Table 1: Descriptive Statistics of Container Freight Data

Variable	Obs.	Mean	Std. Dev.	Variance	Min	Max
SCFI weekly	324	1,154.45	456.95	208,802.80	205	2,164
CCFI weekly	324	1,368.75	296.71	88,035.64	736	1,917
SCFI monthly	75	1,150.19	444.38	197,469.30	320	2,095
CCFI monthly	75	1,368.20	294.43	86,688.05	758	1,897

Former Attempts to Forecast Freight Rates

Forecasting freight rates have been an interesting topic in the shipping industry for a long time. But the literature on forecasting freight rates is quite mature for the bulk shipping industry compared to container shipping industry as maritime researchers and economists are focusing on the container shipping only until recently (e.g. Luo *et al*, 2009, Nielsen *et al*, 2014). Luo *et al* (2009) agreed with Stopford (2009) on the following nature of maritime transportation that freight rates for containerized goods are rather flexible and negotiable. According to them, in times of sudden demand increase, there are many ways to solve the problem, including increasing the cruise speed or increasing loading factor, whereas at the same time, there is a high supply-side flexibility present, too, as shown in Section 2. Thus, for the container shipping industry, we can assert that both demand and supply are flexible enough to confirm the assumption of market equilibrium model by Beenstock and Vergottis (1993). Moreover, "[a]ssuming market clears each year, the freight rate changes with exogenous demand shift caused by the exogenous change in international trade, and the supply shift as more container vessels are added to the world container fleet capacity" (Luo *et al*, 2009, p. 512). Therefore, the demands for container shipping will rise with an increase in international trade even while the freight rate is constant. On the supply side, more container ships are available to serve the demand with the same price as more capacity are added to the industry and this is how the market equilibrium is supposed to be achieved.

Due to the fact that freight rates in the shipping industry are volatile by nature, it attracted even more attention for quantitative analysis. Tinbergen (1959), Zannetos (1966), Strandenes and Wergeland (1982) and Beenstock and Vergottis (1993) are among the pioneers. Stopford (2009) and Luo *et al* (2009) are the pioneers in the container shipping industry, attempting to model the freight rates from a supply-demand framework, and to identify the freight rate determining factors.

Examination of statistical properties of freight rates and the use of autoregressive models to further explore the dynamic relations in freight rates has got a new dimension since Beenstock and Vergottis (1993). There are different types of econometric models suggested by researchers to perform forecast of freight rates. Among those, the ARIMA model (Box and Jenkins, 1976), the Vector Autoregressive (VAR) model (Sims, 1980), the Vector Equilibrium Correction model (VECM) (Engle and Granger, 1987) are the most explored. Stopford (2009) suggested the ARIMA model of Box and Jenkins (1976) for forecasting freight rates in the shipping industry. Cullinane *et al* (1999) applied ARIMA model to a Baltic Freight Index (BFI) dataset, comparing forecast outputs with dataset before and after removal of all handy sized trades from BFI in 1993. Cullinane (1992) found that the most accurate forecast of daily BFI derives from ARIMA models for a forecast period of up to 7 days. Batchelor *et al* (2007) found that ARIMA and VAR models give better forecast for the four routes in the Baltic Panamax Index compared with the VECM models. Benth and Koekebakker (2015) applied continuous time ARMA (CARMA) process for Supramax spot freight rates forecasting. Chen *et al* (2012) applied ARIMA, ARIMAX, VAR and VARX models to forecast spot rates at main routes in the dry bulk market, and found that VAR and VARX models perform better than ARIMA and ARIMAX. To examine volatility in price risk between different sized vessels, Kavussanos (1996) applied the ARCH model. Kavussanos *et al* (2004) investigated the impact of freight forward agreement contacts on spot price volatility in two Panamax Pacific and two Panamax Atlantic trading routes using Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. Li *et al* (2014) used multivariate GARCH model to explore dynamic correlations between shipping spot and derivatives market and to investigate spill over effects.

As mentioned already, Luo *et al* (2009) has made one of the pioneer attempts to forecast freight rates in container shipping industry as others are mostly forecasting forward or spot freight rates for the bulk and dry shipping industry due to greater data availability and market maturity. Luo *et al* (2009) considered yearly container freight rate data from Drewry Shipping Consultants Ltd. (partly derived from Containerisation International's Freight Rate Indicator) from 1994-2008 together with calculated data from a general freight index from ISL (2007) for 1980-1993 and then applied a three stage least square (3SLS) estimated method to forecast container freight rate as a function of fleet capacity for the period 1980-2008. The estimated parameters of this model had a high statistical significance which could be simply due to the fact that their dataset is based on yearly data solemnly, which is of course less volatile than weekly and monthly data. Nielsen *et al* (2014) developed a forecast model for container freight rate reconnoitring the relationship between aggregated market rates (SCFI) and individual liner rates from a case study company. The model focuses on performance and robustness based on observation fit and forecast horizon. However, the model has limitations in explanatory value, which indicates inconsistency in freight rate governing mechanisms over time.

Method and Forecasting Models

As discussed before, forecasting freight rates in the shipping industry has been an important topic for a long time due to the fact that it has always been difficult to forecast accurately owing to a high volatility of the market. Taking this into consideration, our approach of forecasting container freight rates is performed in two steps. Initially, ARIMA models are investigated. In the second step, ARCH is combined with ARIMA to form the ARIMARCH model as ARCH plays a vital role while modelling a volatile time series. We used the statistical software 'R' to perform the forecasts and develop the ARIMARCH model.

ARIMA Model

A non-seasonal ARIMA model is basically the combination of Autoregressive (AR) and Moving Average (MA) models by a differencing operator. An ARIMA (*p*,*d*,*q*) model denotes an ARIMA model with *p* autoregressive lags, *d* non-seasonal difference in order, and *q* moving average lags.

AR models refer to models in which the value of a variable follows habit persistent that is the value in one period is allied to its values in the previous periods. AR (*p*) is an autoregressive model with *p* lags, and is expressed as follows:

$$y_t = \beta + \sum_{i=1}^{p} \emptyset_i y_{t-i} + \varepsilon_t \tag{1}$$

Here, y_t is the container freight rate measured at time *t*, β is the constant, y_{t-i} is the container freight rate of all previous periods until lag p, $\emptyset_i$ is the parameter for y_{t-i} and ε_t is the error term in time *t*.

MA models account for the possibility of a relationship between the value of a variable and the residuals of previous periods. MA (q) is a moving average model with q lags is as follows:

$$y_t = \beta + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{2}$$

Here, ε_{t-i} is the error term of all the previous periods until lag q and θ_i is the parameter for ε_{t-i}. The ARMA model is then a combination of AR and MA models which is as follows:

$$y_t = \beta + \sum_{i=1}^{p} \emptyset_i y_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{3}$$

When a variable is not stationary, a very common solution is to use differenced value of that variable and here comes the integrated part which converts an ARMA model into an ARIMA model. Hence, an ARIMA model is expressed as follows: where $\Delta y_t = y_t - y_{t-1}$

$$\Delta y_t = \beta + \sum_{i=1}^{p} \emptyset_i \Delta y_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{4}$$

In Box and Jenkin's (1976) ARIMA modelling methodology efficient estimation of a statistical model is produced considering the time-dependent nature of the underlying data. As shown in equation (4), ARIMA models are explained by lagged values from previous periods (i.e. auto regression), or residuals lagged from previous periods (i.e. moving-average). Accordingly, "[t]he emphasis of these methods is not on constructing single-equation or simultaneous-equation models but on analysing the probabilistic, or stochastic, properties of economic time series on their own under the philosophy let data speak for itself" (Gujarati, 2003, p. 837).

Accordingly, container freight rates on weekly and monthly levels were checked for stationarity initially via plotting the data and then confirmed by the Augmented Dickey-Fuller Test (Dickey and Fuller, 1981). Data on both levels becomes stationary after 1st difference log operator, although 2nd difference log operator was also checked and confirms stationarity. Then autocorrelation was checked initially via plotting Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) and finally confirmed no autocorrelation in the 1st and 2nd difference log operator time series with the Box-Ljung Test (Ljung and Box, 1978). Although the best ARIMA model for the forecast was supposed to be selected based on lowest Akaike Information Criteria (AIC, Akaike, 1974), six ARIMA models with different (*p*,*d*,*q*) lag orders were investigated regardless of their AIC. Namely, ARIMA (1,1,1), ARIMA (3,1,0), ARIMA (3,1,3), ARIMA (3,2,0), ARIMA (3,2,1) and ARIMA (3,2,2) were the six models investigated before a selection of the best fitting models for weekly and monthly freight rate data was made. It may also be noted that initially 17 different ARIMA models were considered but only six were finally investigated based on their forecast performance and other different lag attributes. Moreover, those ARIMA model with lowest AIC did not necessarily show the best forecast in our case. However, as mentioned in Goulielmos *et al* (2012), many authors such as Kavussanos *et al* (2010), Chen *et al* (2010) etc. also persisted using models such as ARIMA, VECM or GARCH where usual conditions of their use were violated. Accordingly, our selection of ARIMA models here can be justified although those with the lowest AIC should also be acknowledged.

ARCH Model

As ARIMA models deals with data and forecasts in a linear method, it does not incorporate new information or recent changes from the underlying time series. So, while dealing with high volatility present in a dataset, ARCH models are worth further consideration (Engle, 1982). As it is already established that, container freight rate market is one of the most volatile markets, it is relevant to check for ARCH effect on the selected time series for forecasting. There are some methods to check whether ARCH models are applicable for strict white noise and thus can be predicted non-linearly, which were executed accordingly. Here, ARCH models consider current variance of an observation σ_t^2 as a function of the previous error terms. Thus, ARCH model can be formulated as follows:

$$\sigma_t^2 = \alpha + \sum_{i=1}^{m} \alpha_i \varepsilon_{t-i}^2 \tag{5}$$

Here, α is the constant, ε_{t-i}^2 is the nonlinear variance of error terms of all previous periods until lag m and α_i is the parameter for ε_{t-i}^2.

Order and parameters of ARCH models are selected based on lowest *AICc* as follows:

$$AICc = -2 * Log\ likelihood + 2 * (m+1) * (N/(N-m-2)), no\ constant \tag{6}$$

$$AICc = -2 * Log\ likelihood + 2 * (m+1) * (N/(N-m-3)), with\ constant \tag{7}$$

Here, *N* is the sample size after differencing and *m* is the order of autoregressive term. (6) and (7) are implemented to calculate *AICc* after fitting the ARCH models to the residuals.

ARIMARCH Model

We formulated the ARIMARCH model through combing the ARIMA and ARCH technique. It must be noted that, ARCH is not fitted to the original time series or log or differenced log time series as the purpose is to model the noise of only the selected ARIMA models through ARCH to develop the ARIMARCH model. This means ARCH modelled the variance of error terms of selected ARIMA models as a function of previous error terms of those error terms. Six different ARIMARCH (*p,d,q,m*) models are then investigated and applied to make 3 period out-sample forecasts on both data level. Only the best performing forecast models for both SCFI and CCFI on weekly and monthly level are further discussed in the paper. Combining (4) and (5), the ARIMARCH (p,d,q,m) model can be stated as follows:

$$\Delta y_t = \Delta y_t + \sigma_t^2 = \beta + \sum_{i=1}^{p} \emptyset_i \Delta y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \alpha + \sum_{i=1}^{m} \alpha_i \varepsilon_{t-i}^2 \tag{8}$$

Empirical Analysis and Findings

The best performing forecast model for SCFI weekly, CCFI weekly, SCFI monthly and CCFI monthly turned out to be ARIMARCH (3,1,0,3), ARIMARCH (3,1,3,5), ARIMA (3,2,0) and ARIMA (3,2,0) respectively. Figure 2 presents actual, fitted and forecasted freight rates. Fitted freight rates are estimated values of the previous time periods based on the selected forecast models. However, a) in Figure 2, the fitted values differ largely with the actual values starting from the week 196 (12/07/2013) as the SCFI jumped from $514 per TEU in week 194 (28/06/2013) to $1,409 per TEU in week 195 (05/07/2013) on the Shanghai to Northern Europe route. Accordingly, the fitted value also increases dramatically in the ARIMARCH (3,1,0,3) model selected for SCFI weekly. Just after two years (on 12/06/2015), SCFI from Shanghai to Northern Europe dropped to an all-time low of $243 per TEU and it even could fall to $150 per TEU (ALPHALINER, 2015). Moreover, this was significantly lower than the breakeven level of $800 per TEU as estimated by ALPHALINER (2015) for this route. In this situation, carriers skipped 52 sailings in total on the Far East – Europe trade lane during the first 6 months of the year 2015. However, as carriers are always reluctant to permanently reduce supply capacity, freight rate may not recover. Although, our proposed forecasting models perform better compared to existing models, it is still tough to accurately forecast such dramatic swings of freight rate in liner shipping.

Hereafter, based on (8), the final selected models to forecast the container freight rates for SCFI and CCFI on both weekly and monthly levels are written as follows:

SCFI Weekly [ARIMARCH (3,1,0,3)]:

$$\Delta y_t = -0.0993\Delta y_{t-1} - 0.2195\Delta y_{t-2} - 0.2108\Delta y_{t-3} + 0.001151 + 1.133267\varepsilon_{t-1}^2 + 1.949304\varepsilon_{t-2}^2 + 0.503134\varepsilon_{t-3}^2 \tag{8}$$

CCFI Weekly [ARIMARCH (3,1,3,5)]:

$$\begin{aligned}\Delta y_t = {} & 0.1815\Delta y_{t-1} + 0.3320\Delta y_{t-2} + 0.0933\Delta y_{t-3} + 0.1828\varepsilon_{t-1} - 0.2266\varepsilon_{t-2} \\ & - 0.1866\varepsilon_{t-3} + (4.93E - 04) + (2.28E - 18)\varepsilon_{t-1}^2 \\ & + (1.00E - 01)\varepsilon_{t-2}^2 + (1.03E - 01)\varepsilon_{t-3}^2 + (8.54E - 02)\varepsilon_{t-4}^2 \\ & + (1.18E - 01)\varepsilon_{t-5}^2\end{aligned} \tag{9}$$

SCFI Monthly [ARIMA (3,2,0)]:

$$\Delta\Delta y_t = -0.6519\Delta\Delta y_{t-1} - 0.4502\Delta\Delta y_{t-2} - 0.4185\Delta\Delta y_{t-3} \tag{10}$$

CCFI Monthly [ARIMA (3,2,0)]:

$$\Delta\Delta y_t = -0.0725\Delta\Delta y_{t-1} - 0.3449\Delta\Delta y_{t-2} - 0.2786\Delta\Delta y_{t-3} \tag{11}$$

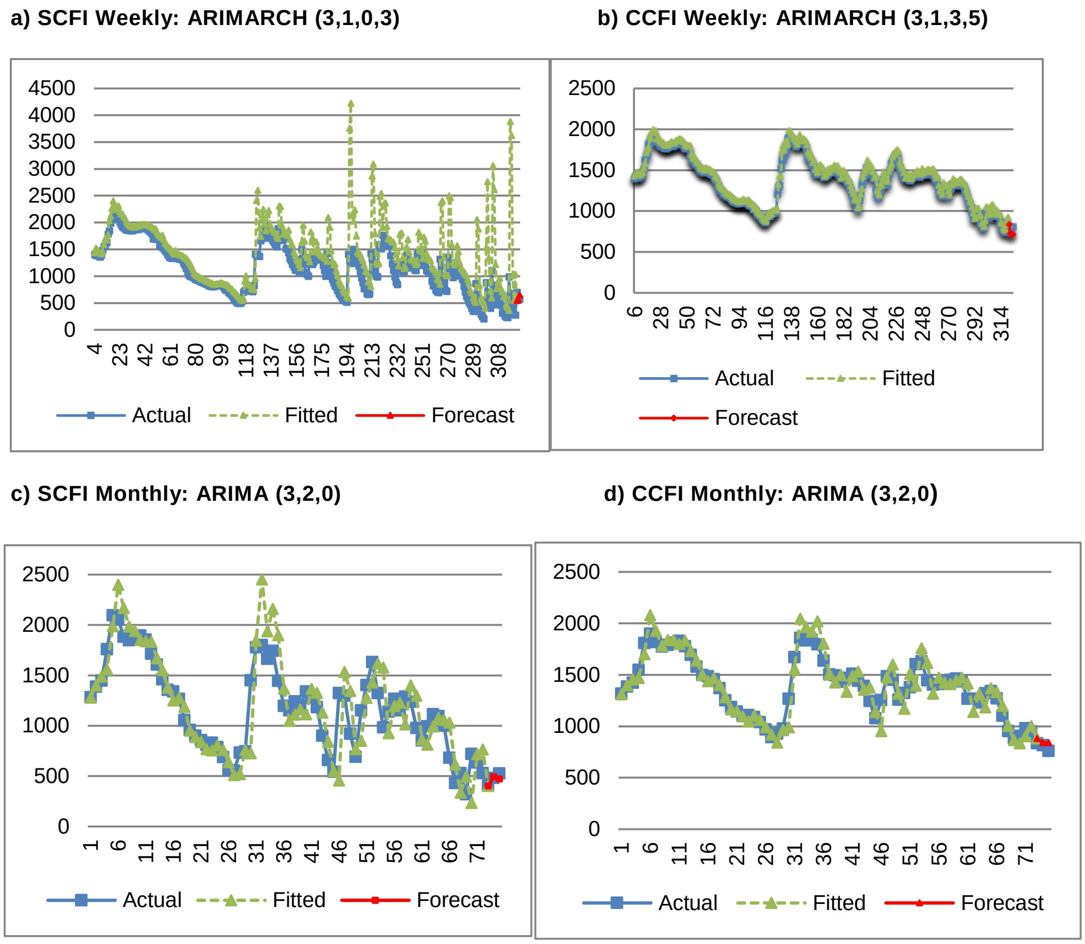


Figure 2: Models Forecast Performance

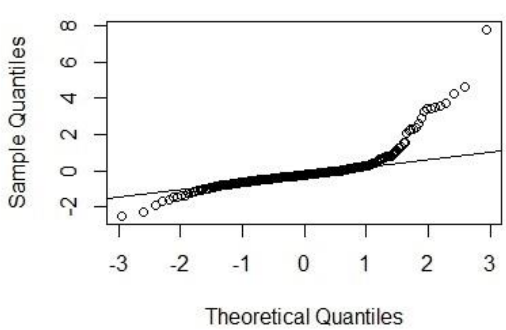
Diagnostic Check of the Models

All the selected forecasting models need to go through diagnostic checks to be valid for forecasting. Accordingly, these four best performing selected forecasting models have been checked for autocorrelation of their residuals using the Box-Ljung Test (BLT, Ljung and Box, 1978), and also checked for normality of their residuals through Jarque-Bera Test (JBT, Jarque and Bera, 1980) along with the demonstration of QQ plots.

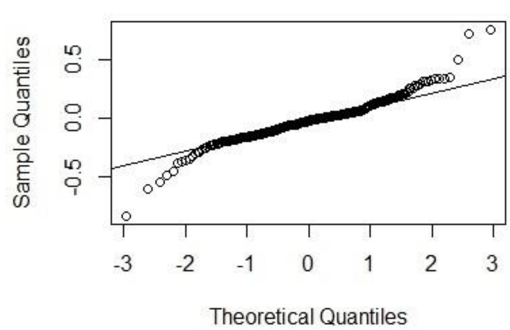
Table 2: Box-Ljung Test and Jarque-Bera Test

Index	Selected Models	Lag	BLT p-Value	JBT p-Value
SCFI weekly	ARIMARCH (3,1,0,3)	10	0.3143	< 2.2e-16
CCFI weekly	ARIMARCH (3,1,3,5)	10	0.1039	< 2.2e-16
SFCI monthly	ARIMA (3,2,0)	10	0.3898	< 2.2e-16
CCFI monthly	ARIMA (3,2,0)	10	0.5073	<2.581e-08

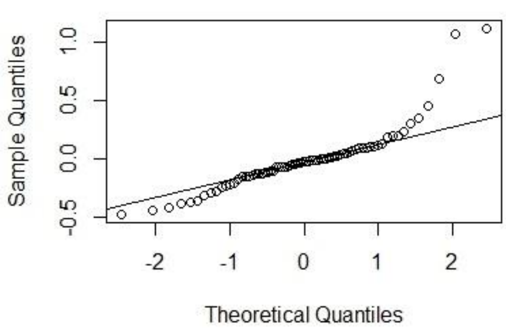
a) SCFI Weekly



b) CCFI Weekly



c) SCFI Monthly



d) CCFI monthly

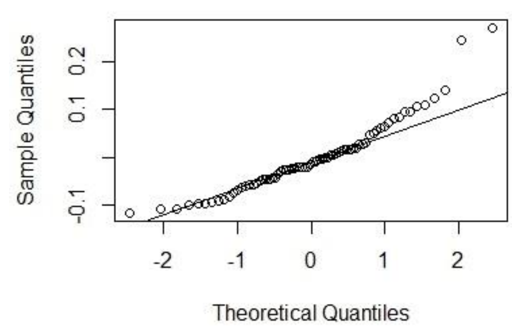


Figure 3: QQ Plot of Forecast Model Residuals

Table 2 presents the results of BLT for autocorrelation of the four selected models with H_0: 'there is no autocorrelation in the time series data'. As all p-values of the four selected models are well above the 5% level, H_0 is accepted. Therefore, there is no autocorrelation in the residuals of each of the selected forecasting models. Concerning JBT, in all four cases the p-values are less than 5%, which leads to a rejection of H_0: 'the residuals are normally distributed'. Therefore, the QQ plots of residuals are plotted (Figure 3) to visualize the normality of residuals of the selected forecasting models. Although, JBT does not support normality, but it can be noticed from the QQ plots that the residuals of the four selected forecasting models seem to be fairly normally distributed though with fat tails.

Forecast Performance

Forecast accuracy based on Mean Error (ME), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Percentage Error (MPE) and Mean Absolute Percentage Error (MAPE) for the four selected forecasting models are shown in Table 3.

Table 3: Forecast Performance

	SCFI weekly	CCFI weekly	SCFI monthly	CCFI monthly
Accuracy Measures	ARIMARCH (3,1,0,3)	ARIMARCH (3,1,3,5)	ARIMA (3,2,0)	ARIMA (3,2,0)
ME	28.54	42.68	14.36	-51.39
MAE	76.45	42.68	22.32	51.39
RMSE	99.70	55.77	31.66	56.00
MPE	3.29	5.42	2.68	-6.51
MAPE	11.65	5.42	4.33	6.51

Further Discussion

Being agreeing with Verbeek (2008) we believe that, simple models with univariate time series of data forecast are always better than more complicated models. Accordingly, we suggest the ARIMARCH (*p*,*d*,*q*,*m*) model for future forecasts as it performs better with the given volatility and recent changes in the underlying times series data of SCFI and CCFI from Shanghai or Chinese hub ports to Northern Europe, especially in our time frame from 16/10/2009 to 25/12/2015.

While developing time series forecast models, there is always an implicit assumption that future values will somehow be related to the past ones. This assumption is virtually based on "weak form tests" according to Fama (1970), in which available information is just the previous price or return sequences. Alike in financial markets, we can always rely on the efficient market hypothesis as long as the working mechanism of container freight markets leads to a supply-demand balance. Moreover, "[t]he theory of efficient market is concerned with whether prices at any point in time 'fully reflect' available information" (Fama, 1970, p. 413). In the container shipping industry, freight rates reflected publicly available information like GRIs over the last 5 years. This seems to be the main reason for higher volatility in spot rates like the SCFI, which would be the case of "semi-strong tests" according to Fama (1970). However, the expected value GRIs should have not been considered as granted as it is just a single possible indicator of container freight rates. Therefore, the container freight rates are observed to dramatically increase and also drop very quickly. On the contrary, the movements other way around do not occur at all.

One more aspect to consider is that alike financial markets, shipping markets are also influenced by psychological factors than only the efficient market assumption. So, the best possible way in forecasting the container freight rate seems to balancing a number of trade-offs to achieve satisfactory performance. In order to develop a robust and operational forecast model for shipping companies, Nielsen *et al* (2014) mentioned that the model should be able to forecast at least six weeks out-sample with a MAPE of less than 5%. The approach developed in our paper results in forecasting three weeks out-sample for both the SCFI and CCFI on weekly and monthly level which is fairly comparable with 5% MAPE, although MAPE for SCFI weekly is 11.65%. But this weak performance can be at the same time easily explained by the aforementioned attempts of carriers to raise the base rate through GRIs (ALPHALINER, 2013*c*). As we can see in Figure 2, fitted values were in line with the actual values till week 124 ($826 on 02/24/2012) followed by a dramatic increase in week 125 ($1,412 on 03/02/2012) on the Shanghai to Northern Europe route. Then another dramatic fluctuation occurred again from week 194 ($514 on 06/28/2013) to week 195 ($1,490 on 07/05/2013), and thereafter similar effects can be noticed in weeks 290, 302, 315 and 321. In all these cases, SCFI suddenly increased dramatically (more than $500 approx.) from one week to another basically due to GRI announcements by carriers. But because of overall market conditions, SCFI went down subsequently in the weeks after and so they failed. Overall, it can be assumed that MAPE for SCFI weekly could be within this 5% range, too, if the carriers would stop announcing GRIs in the future as demanded by EC (2016). The ARIMARCH (p,d,q,m) model is therefore regarded to give better forecasts with satisfactory performance for both the long as well as the short term.

Conclusions and Future Research

This paper investigated container shipping freight rate dynamics and suggests a forecasting model called “ARIMARCH” to forecast them. ARIMARCH is a combination of ARIMA and ARCH models. The ARCH part of the model is not fitted to the actual time series as the principal purpose of ARCH here is to model the noise of only selected ARIMA models to construct the ARIMARCH model. SCFI and CCFI, each on weekly and monthly levels, are forecasted for three out-sample periods. We have chosen both weekly and monthly level because operational decisions by carriers like the supply-side flexibility tactics described in Section 2 always take some time to affect the supply-demand balance while monthly forecasts for three periods can provide insights for decisions making on quarterly basis. Our four best-performing forecast models are ARIMARCH (3,1,0,3) for SCFI weekly rates, ARIMARCH (3,1,3,5) for CCFI weekly rates, and ARIMA (3,2,0) for both SCFI and CCFI monthly rates on the Shanghai or Chinese hub ports to Northern Europe trade lane for the time period between 16/10/2009 and 25/12/2015. With the notable exception of SCFI weekly, MAPE for all our selected models are fairly comparable with the 5% level argued by Nielsen *et al* (2014). However, a high MAPE of 11.65% for SCFI weekly is better compared to the results of other existing forecasting models for such a volatile time series. Moreover, this is in turn easily explainable by GRI announcements which frequently failed due to overall market conditions as described in Section 2. Therefore, it can be assumed that MAPE for SCFI weekly will probably be within a 5% range, too, in the future if the liner shipping companies stops announcing GRIs as demanded by EC (2016).

As outlined in the present paper, high forecast accuracy and a good model fit for business operations is to be expected by our ARIMARCH model. However, the quest for better forecasting models is still demanding, so future research may consider to include a combined model of ARIMA and GARCH. Furthermore, out-sample forecast for long-term periods should be tested using the ARIMARCH model, which may suit better for strategic decision making of the liner shipping companies and other players in the container shipping industry. Multivariate time series models including other explanatory variables than those freight rate indices employed for the ARIMARCH model and neural network models to forecast container freight rates are also thinkable. Last but not least, future forecast models should be checked for robustness in implementing over different forecast horizons.

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