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Ονοματεπώνυμο: Βολίκα Κασσιανή

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Athens University of Economics and Business
47A Evelpidon St and 33 Lefkados St, Athens 11362, Greece
http://www.aueb.gr/

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«Δηλώνω υπεύθυνα ότι η συγκεκριμένη πτυχιακή εργασία για τη λήψη του Μεταπτυχιακού Διπλώματος Ειδίκευσης στη Λογιστική και Χρηματοοικονομική έχει συγγραφεί από εμένα προσωπικά και δεν έχει υποβληθεί ούτε έχει εγκριθεί στο πλαίσιο κάποιου άλλου μεταπτυχιακού ή προπτυχιακού τίτλου σπουδών, στην Ελλάδα ή στο εξωτερικό. Η εργασία αυτή έχοντας εκπονηθεί από εμένα, αντιπροσωπεύει τις προσωπικές μου απόψεις επί του θέματος. Οι πηγές στις οποίες ανέτρεξα για την εκπόνηση της συγκεκριμένης διπλωματικής αναφέρονται στο σύνολό τους, δίνοντας πλήρεις αναφορές στους συγγραφείς, συμπεριλαμβανομένων και των πηγών που ενδεχομένως χρησιμοποιήθηκαν από το διαδίκτυο».

Βολίκα Κασσιανή

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Abstract

In the present dissertation, volatility comparison took place among freight rates of major routes of Container market and among different ship categories such as dry bulk, tanker and container ships. The final sample consists of weekly prices of several freight rate indices that cover the period from 2003-2016. Volatility was measured by the conditional coefficient of variation (CCV) which was calculated by dividing conditional standard deviation over absolute actual returns. Conditional standard deviation, in a time-varying framework, was extracted with the use of ARMA-GARCH (and others related) models. Applying SIC criterion, the best model for both conditional mean and conditional variance was selected in order to conclude to an adequate model that could accurately represent conditional standard deviation.

Using CCVs of each time-series as a proxy of volatility their mean level was compared among routes and among indices. More particularly, estimated mean values were compared in a context of parametric tests and estimated medians were compared in a context of non-parametric tests.

As it concerns the Container Market, results showed that routes involving big seas, like Pacific and Atlantic Ocean, were found to perform the higher volatility in freight rate returns compared to the volatility of routes involving not so big or regional seas. In addition, we concluded that the longer the distance, the higher the uncertainty.

As it concerns the different freight markets, the same methodology was applied. Results revealed that BDI performed the highest volatility, followed by BDTI, BCTI and finally CCFI.

I. Introduction

1.1 Motivation

Although a certain amount of the world trade is transported by airplane, rail or truck, most are carried by ships. Shipping serves almost the 90% of international trade needs and it is obvious that is a vital industry for the economic development. Moreover, it is an excessive volatile and capital intensive market, and thus, proper handling of all its aspects is essential to ensure profitability and affordability to those involved. This global business is influenced by political shocks and economic fluctuations around the world and the volatile nature of the freight market is due to its highly competitive characteristics where freight rates depend on the balance of demand and supply.

Uncertainty is the main characteristic of seaborne trade. To be more understandable about uncertainty, an example is given; the volume of trade is constantly changing. So, it is hard for the shipowners to decide when is the better period to buy new ships or to scrap the old ones. If new ships are built but the trade decreases, the shipowners' investments would be devastating having their ships idle on the ports and freight rates would fall as an effort to minimize the loss. On the other hand, if there are not that many ships available but trade grows up, eventually, that could lead to no exports and generally to no economic growth. However, the few available ships would gain a fortune by charging the transportation at will. (Stopford 1997) This example shows us the notion of shipping risk and explains to us that it is a major issue for all participants in the shipping industry.

This complexity and uncertainty of that industry, have urged scholars to discover the secrets of freight markets. In fact, from the early thirties, shipping communities have expressed a strong interest in quantitative analysis of freight rates. Particularly, freight rate modelling has been of primary interest. Once the model is formulated, it can be used for forecasting purposes. Even if a large amount of research into shipping freight markets has been done, "*there is no example of a successful freight rate forecasting model*" (Veenstra, 1999). This is the reason why freight rate modelling and forecasting remains a fascinating topic.

Kavussanos, Visvikis and Goulielmou (2007) support that shipowners face numerous risks such as fluctuation in freight rates, interest rates, vessel value prices, bunker rates and foreign exchange rates. For the purpose of this dissertation, we only study about the fluctuation of freight rates.

1.2 Purpose of the study

This thesis initially focuses on one shipping segment that (to the author's knowledge) has little evidence of prior research. The containership market, although it is not as attractive as the dry bulk or tanker market, it still represents the 12.8% [1]of the total world fleet and stands third after the two segments mentioned above with 42.9% and 28.5% of the total world fleet respectively. The first aim of this thesis is to model and compare the volatility of the CCFI and its routes. The second part of this thesis will attempt to model and compare the volatility among the Shipping Freight Markets and more specifically among CCFI, BDI, BCTI and BDTI.

1.3 Structure

This paper is organized as follows. Chapter 2 is a brief outlook of the literature, providing information about early and modern econometric modelling of freight markets as well as a brief market analysis of the three main shipping markets. Chapter 3 analyzes the data sample used to conduct this research. Chapter 4 documents the methodology employed which includes univariate time series modelling techniques. Finally, Chapter 5 contains the empirical results of this thesis, followed by a conclusion in Chapter 6.

1 According to Unctad Review of Maritime transport 2014.

II. Literature Review and Shipping Market Analysis

2.1 What is the freight market?

As Stopford (1997) pointed out, the freight market is the marketplace where sea-transport is bought and sold. Shipowners have ships available for hire, charterers have cargo to transport and shipbrokers put the deal together. According to Stopford (2009), Freight market can be furtherly divided into three parts;

- The voyage charter (*spot charter*), in which the shipowner can sell the transport at a fixed price per ton of cargo for a particular route.
- The time charter[2] market, in which the ship is hired for a specific period of time.
- The freight derivatives market: Freight Derivatives are financial instruments for trading at future levels of freight rates and are settled against numerous freight rate indices.

All these three markets create freight revenues for shipping investors' which are the main source of cash in the shipping industry. For the purpose of this study, only the voyage market will be examined.

2.2 Literature Review

According to Gray (1987), the greatest risk in the shipping industry is the freight rate risk as the most important uncertainties affect revenues rather than costs. Investment decisions in the shipping market are entirely dependent on the movement of freight rates. For that reason, it is necessary to understand this mechanism to provide long-run and stable business operations.

2.2.1 Early econometric modelling of freight markets.

As mentioned by Glen and Martin (2005) the efforts for modelling the freight rate market started in the *1930s* with Tinbergen (1931, 1934) and Koopmans (1939). Tinbergen (1931) investigated the sensitivity of freight rates to changes in the level of

2 In a time charter agreement, the charterer has the absolute operational control of the ship. The usual time charter agreement has a duration of months or maybe years. The charterer pays all voyage expenses, such as bunkers, canal dues, port expenses etc. Although a time charter contract seems riskless, as the daily cash flows for both the charterer and the shipowner are known, in practice, time charters are complex and they do involve risk for both parties.

demand and the factors affecting supply. Finally, he concluded that freight rate could be written as:

$$F = e_1q - e_2K + e_3P_b$$

Where q is the demand, K is the vessel's size, P_b is the bunker prices (coal) and $e_1 = 1/\gamma$, $e_2 = \alpha/\gamma$ *and* $e_3 = \beta/\gamma$. He used data from 1870-1913 to estimate the unknown parameters and he concluded that the above equation could be written as:

$$F = 1{,}7q - 1{,}6K + 0{,}4P_b$$

He additionally, in 1934, created a model of the freight rate market of the following form:

$$F(t) = -\ rK(t)$$
$$DK(t) = Q(t - \ u)$$
$$Q(t - u) = lF\ (t - u)$$

where $F(t)$ is the freight rate at time t, $K(t)$ is the level of tonnage, Q represents the ship orders, u is the lag between ordering and delivery and D is the difference operator. Finally, by solving this differential equation, he concluded that:

$$DK(t) = -\alpha K\ (t - u)$$

Which means that if the parameters α is of the correct value, it will generate cycles over time.

Koopmans (1939) investigated the determinants of tanker freight rates and proposed the short term supply curve which is characterized as inelastic when tonnage is in full employment and elastic when tonnage is unemployed. When Q_{supply} is greater than Q_{demand}, then, freight rates fall, more ships are laid up and speed starts to slow down. The opposite happens when demand is greater to supply.

Zannetos (1966) was (to the author's knowledge) one of the first scholars of the tanker market. He investigated the relationship between spot rates and time charters. He suggested that the spot tanker rates should be related to the long run marginal cost of tanker services. He also pointed out that voyage charter rates follow a random walk model.

Wergeland (1981) proposed a model for dry bulk ships which is known as "Norbulk". This model consists of both supply function (similar to the Tinbergen model) and demand for ton-miles function that is assumed to be negatively related to freight rates and positively related to the level of global trade. This model was formulated based on data for 1965-1985 and was structured as follows:

$$Q_{dem} = VF$$
$$Q_{sup} = FB_{fd}Foi$$

where Q_{dem} = Demand for dry bulk (tonnes per mile)

Q_{sup}= Supply for dry bulk (tonnes per mile)

V = Volume of sea trade of dry cargo by tone

F = Freight rate index of dry bulk ships

B_{fd} = dwt of the trading dry bulk ships

Foi= Average price of fuels

In order for the model to be linear, the natural logarithm of the variables was used on both sides of both equations. The estimated model was:

$$Q_{dem} = 1.379V - 0.077F$$
$$Q_{sup} = 0.272F + 0.485B_{fd} - 0.127Foi$$

The model indicates that the demand is slightly affected by freight rates.

In a series of Beenstock and Vergottis (1989a, b, 1993a, b) research papers, freight rate is determined by the interaction of supply and demand.

$$Q_s = f_1 (F_v, FR / P_b, Z_s)$$

Where freight rates move in order to set demand equal to supply.

$$Q_D = Q_S$$

Finally, $FR=f_2 (F_v, Q_D, P_b)$

Where Q_s is the supply of dry cargo (measured in ton-miles), Q_D is the demand, F_v is the active fleet, *FR* is the freight rate for dry cargo voyage, P_b is the unit voyage costs (mainly consists of bunkers but is also includes port charges and crew costs). They used daily data from 1950 to 1986.

2.2.2 Modern econometric modelling of freight markets.

The evolution of econometric approaches and techniques led to changes in modelling of bulk shipping markets. First of all, the structural models were replaced by autoregressive models and the researchers focused on the stationarity properties of the data. They realized that overpassing the order of integration of time series would have disastrous consequences in the empirical work.

2.2.2.1 Previous research in the Dry-Bulk sector

By far the most academic interest has been shown in the bulk shipping industry, and this is because there is an index that is daily updated namely the Baltic Dry index. For example, Kavussanos (1996a) applied the ARCH model to shipping markets for the first time to measure the volatility in the Dry-Cargo sector (Handysize, Panamax, Capesize) for both spot and time-charter rates. He used monthly data from 1973 to1992. He finally reached to the conclusion that risk is higher in the time-charter market and he supported that larger vessels have higher volatility than the smaller ones.

Kavussanos (1997) examined the dynamics of conditional volatilities in the world dry-bulk market for second-hand ships. He used monthly data for second-hand prices and time-charter rates for 5-year-old Capesize, Panamax and Handysize vessel from January 1976 to August 1995 by building an ARCH model. He pointed out that the price of larger vessels has higher volatility than the price of smaller ones.

Veenstra and Franses (1997) tried to forecast freight rates in the dry bulk sector using data that covered the period from 1983-1993 with the Vector Autoregressive Model, but although there were long run relationships between freight rates, their forecasts seemed not to be promising maybe due to a stochastic trend.

Chen and Wang (2004) applied E-GARCH model to investigate the presence of the leverage effect (asymmetric volatility) in the international bulk shipping market. They used daily data from April 1999 to July 2003 for four time charter routes and they concluded that the phenomenon of leverage effect does exist. The coefficient δ

indicated a negative sign which means that the positive shocks generate less volatility than negative shocks.

Batchelor et al. (2007) found that ARIMA and VAR models are better in forecasting the BDI's routes than the Vector Error Correction Model (VECM), while, in contrary, Kavussanos and Nomikos (2003) came to the opposite conclusion; they found that the VECM performs better forecasts.

Lu et al. (2008) used the daily returns of three different types of bulk vessels (Capesize, Panamax and Handysize) over the period from March 1999 to December 2005 to investigate the characteristics of volatility. They applied the GARCH model and showed that external shocks have a tendency to strengthen for all the three series. In addition, they divided their sample into two periods (March 1999-December 2002, and January 2003-December 2005) to examine the asymmetric impact of past innovations and current volatility by applying the E-GARCH model. They reached the conclusion that asymmetric characters are distinct for different market conditions and different vessel size segments.

Zhai and Li (2009) examined the volatility of BDI using GARCH type models with different distributions. They reached the conclusion that GARCH(1,2) model with Student-t distribution is the best to fit the volatility and T-GARCH(1,2) with normal (Gaussian) distribution is more appropriate to describe the leverage effect of BDI.

More recently, Xu et al. (2011) studied the relationship between the time-varying volatility of the dry bulk freight market and the change in the supply of fleet trading. They used monthly data from Panamax and Capesize spot and one-year time charter rates as far as the fleet size of Panamax and Capesize, the industrial production and the bunker price that cover the period from 1976-2010. They firstly used an AR-GARCH model to measure the freight rate volatility and secondly they used a GMM regression to investigate the relationship between freight rate volatility and fleet size growth. They finally confirmed that the volatility of both time-charter rate and spot rate in the dry bulk markets is time-varying and that the change in fleet size positively affects the freight rate volatility.

Yang et al. (2011) examined the volatility of four Baltic Dry Bulk indices (BCI, BPI, BSI and BHSI) by using the GARCH (1,1) model. They found out that this model could reflect the persistence of fluctuation very well.

Geman and Smith (2012) studied and modeled the dynamics of BDI covering the period from 1988-2010. They found that the standard deviation of annualized returns that cover the period from 2003-2010 was more than 60% and that was a number never experienced before in the stock market. That is explained by the fact that until 2008 there was an extremely rise of freight rates and since then, a dramatic fall. They also noted that periods of high volatility are followed by a more stable period that lasts a few months.

Fan et al. (2012) studied the volatility spillover effect among Capesize, Panamax and Handysize by using the multivariate GARCH. They concluded that the Capesize has volatility spillover effect on Panamax and Handysize while Handysize and Panamax do not have volatility spillover effects in Capesize.

Chen et al. (2012) made an attempt to forecast spot rates for three types of dry bulk vessels using the ARIMA ARIMAX, VAR and VARX models were employed in the article to make forecasts with data that covers the period from 1990-2010. They reached the conclusion that the VAR and the VARX models performed better forecasts than ARIMA and ARIMAX model

Fan et al. (2014) studied the Baltic Capesize Index (BCI). To analyze volatility persistence the GARCH (1,1) model was introduced. This model was used for forecasting the BCI returns.

Dai et al. (2015) made an empirical analysis of freight rate and vessel's price volatility in the dry bulk market. Their data consisted of monthly time series of one-year time charter rates, newbuilding and secondhand vessel prices during 12/2001 to 11/2012. They used a tri-variate GARCH model which could incorporate three independent variables, as a univariate GARCH cannot investigate the dynamic volatility transaction among different time series. They concluded that a BEKK-GARCH (1,1) model captured the volatility transmission effects. In addition, they supported that the freight rate volatility is influenced by the secondhand vessel market and that the newbuilding market is indirectly affected by freight rate and secondhand vessel price volatility. Finally, they support (as many other researchers) that the freight rate market is the most volatile market, while the newbuilding market the least.

2.2.2.2 Previous research in the Tanker market

Other studies have examined the volatility of the tankers. Kavussanos (1996b) reviewed the volatility in the world tanker market for the price of second-hand ships by applying the ARCH model. The conditional mean was defined as the changes in price through ARIMA-X form models. He modeled and compared the dynamics of time-varying volatility between different size vessels and he concluded that bigger tanker ships (VLCC) seem to have higher volatility than smaller size vessels as Suezmax and Aframax.

Glen and Martin (1998), following Kavussanos's attempts, did a relevant research and estimated the conditional volatility in the tanker market by size categories and types of time-charter contracts, but the estimation of conditional mean has been done by a different model.

Kavussanos (2003b) also employed the GARCH model to examine the risks in the tanker freight market. He used monthly data from 1979 to 1994 for the one-year time-charter rates and spot freight rates. He finally concluded that time-charter markets are less volatile than the spot market and smaller vessels seem to be less volatile than larger too.

Kavussanos and Dimitrakopoulos (2007), investigated the issue of market risk measurement in the tanker segment, by employing an Extreme-Value (EV) concept and a Filtered Historical Simulation (FHS) approach. They concluded that EV and FHS were the best models for short-term daily risk forecasts as they produced accurate results.

Alizadeh and Talley (2011) used tanker shipping contracts from January 2006 to March 2009 to estimate freight rates and laycan[3] periods. They used a system of simultaneous equations, and they concluded that the duration of this period is crucial for the determination of shipping freight rates. They also found that vessel's age, voyage routes vessel's type and the fixture deadweight utilization ratio seem to determine freight rates too.

3 Laycan is the period within the vessel should arrive at the port and be ready for loading. If the vessel arrives later than the laycan period, charterers are entitled to exercise the option and cancel the charter-party.

2.2.2.3 Previous research in the Containership market

We can difficulty find studies based on container ships and this is because dry cargoes and tankers are the most widely known means of seaborne trade of commodities worldwide. Despite this, Luo et al. (2009) investigated the fluctuation of the container freight rates due to the interaction between supply and demand for container transportation services. They used data from 1980-2008 to apply the three-stage least square method. Finally, their estimated model tends to explain more than 90% of the variations in fleet capacity and the freight rate.

Zhu and Zhao (2013) investigated the volatility of CCFI by using the ARCH family models for weekly data that covered the period from January 2000 to August 2012. The GARCH model was used to describe the volatility clustering and then the E-GARCH model was used to analyze the asymmetry of CCFI. They found out that the container freight rate had an anti-leverage effect.

Another study is by Chang (2015) and has focused on the CCFI and the HRCI[4] for long memory testing in volatility and the models concerning the long memory effect. He applied tests as FIGARCH, HYGARCH and FIAPARCH in data that cover the period from 2000-2014 for the HRCI and from 2007-2014 for the CCFI. He reached the conclusion that precise estimates of containership freight indices may be acquired from a long-memory in volatility models with skewed Student-t and Student–t distribution. He also suggests that such models improve the long-term volatility forecasts and that this could be useful to risk management in the container freight market.

2.2.2.4 Previous research that compares Dry-Bulk with Tanker and Containership freight market

Stopford (1997) pointed out that although the freight rates in containers, tankers and bulk carriers, in the short run, behave differently, in the long run, changes in the freight of one type of ship would affect the freight of the other types, as they are all at the same transportation sector**.**

Kavussanos and Alizadeh (2002) used the GARCH-in-mean model and examined a variety of ship sizes and charter lengths from 1980-1997. They wanted to

4 Howe Robinson Container Index (HRCI) reflects the container market charter rates and is issued by the Howe Robinson & Co. Ltd, one of the world's largest independent brokerage firms for containerships and bulk carriers.

investigate, according to the expectation hypothesis, whether long-term charter rates are a function of a series of short-term contracts. That means that the present value of the cash flows from a time charter contract should be equal to the present value of the expected cash flows from some spot contracts with the same duration. They did find that the results do not support the expectation hypothesis for the period given and that the spot market is riskier due to spot market volatility, utilization risk, transport shortage risk, default risk, etc.

Adland and Cullinane (2005) did a relevant research and also concluded that the expectation hypothesis can be rejected and that the risk premium must be time varying for the bulk freight market.

Koekabakker et al. (2006) did a research about stationarity in spot and time-charter rates for both tanker and dry bulk market over the period 1990 to 2005. They performed both linear and non-linear models such as augmented Dickey-Fuller tests and KPSS test to detect if there is a serial correlation in variables. They concluded to different results with each model as standard unit root tests are widely known to have lower power than nonlinear alternatives. Despite that, the final result was that freight rates are non-stationary.

More recently Angelidis and Skiadopoulos (2008) applied the Value at Risk approach and parametric (e.g. GARCH) and non-parametric (e.g. historical simulation) models for dry and wet cargoes to measure the freight rate risk. Their results were that the freight rate risk is greater in the wet cargo markets and in general, freight rates are much more volatile than other assets.

Alizadeh and Nomikos (2011) examined the weekly average of spot rates as well as one-year and three-year time charter rates for three different dry bulk carriers[5] and three different tankers[6] that cover the period from 1992-2007. They used augmented EGARCH models to investigate the significance of the dynamics of the term structure and its effects on time-varying volatility. They came to the conclusion that when the market is in contango[7], the volatility is lower compared to when the market is in normal backwardation[8].

5 The three bulk carriers are classified according to their size and capacity. (Capesize, Panamax, Handymax)

6 The three tankers are also classified according to their size and capacity. (VLCC, Suezmax, Aframax)

7 Contango refers to a situation where the futures contract price is higher than the expected spot price.

8 Backwardation refers to the market condition where the futures contract price is below the expected future spot price at contract maturity.

Drobetz, et al. (2012) examined whether asymmetric effects or shocks of macroeconomic variables are more suitable to explain the time-varying volatility in the tanker and dry bulk market by using the GARCH and E-GARCH models. Their sample period was from March 1999 to October 2011 and their data consisted of the Baltic Exchange Indices. They finally pointed out that a) there are no asymmetric effects in the dry bulk market, but these effects are strongly pronounced in the tanker freight market b) Macroeconomic variables should better be embodied into the conditional variance equation rather than into the conditional mean equation and c) the assumption of t-distribution performs better than the Gaussian.

Chou et al. (2013) investigated the return lead-lag and volatility transmission between dry-bulk and container shipping freight by testing the BDI and the CCFI that had been divided into three sub-periods; before, during and after the financial crisis of 2008. They used the bivariate GARCH-BEKK model and they suggested that there is a long-run equilibrium relationship in the full sample although the financial crisis of 2008. In addition, the two indices have at least one cointegrating vector before the crisis that is maintained and after. Granger causality tests indicate that there is no significant lead-lag relationship in the full sample period.

2.3 International Shipping Market Analysis

2.3.1 Containership Market

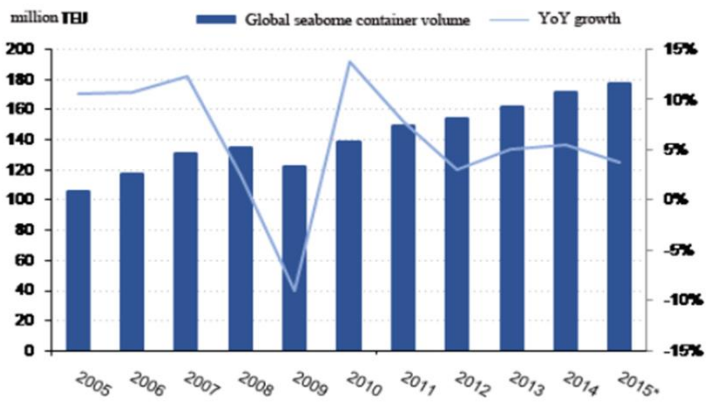
According to the annual report of Shanghai International Shipping Institute for the year 2015-2016, the CCFI hit an average long-term historical low as of December 25, at 875.53 points, lower than the historical low in 2009 of 879.01 points and registered a plummet of 19.39% compared to 2014. All the main, secondary and near-sea shipping lines suffered declined freights in 2015 mainly due to reduced cargo transportation demand that forced the shipping companies to lower their prices. The following graph represents the trend of CCFI in 2015.

Data Source: *Shanghai Shipping Exchange, prepared By Shanghai International Shipping Institute*

In addition, a massive increase in deliveries of large ships was noticed, and so, both these two factors led to a surge in transportation capacity supply and therefore to reduced freight rates. The report indicates that as of 2015, the average ship size of global container fleets reached 3.644 TEU and the global container transportation capacity stood at 21.868 mil TEU (that corresponds to an increase of 5.59% and 7.06% respectively than in 2014).

The global seaborne container volume stood at 177.7 million TEU in 2015, a y.o.y increase of 3.68%. The growth rate was slower than the 5.54% in 2014.

Global Seaborne Container Volume



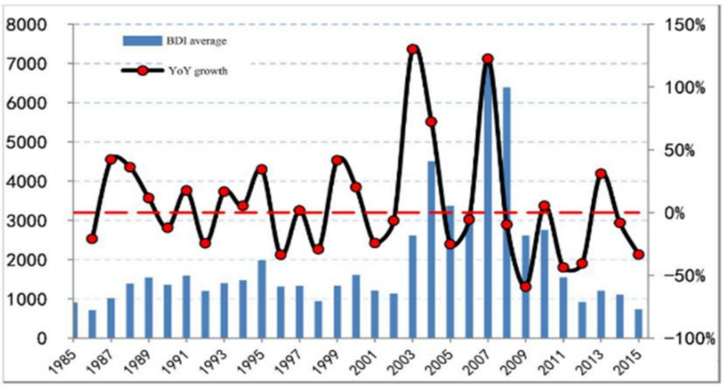
Data Source: *Clarksons Research, prepared By Shanghai International Shipping Institute*

The regional and south-north routes enjoyed a strong volume growth of 4.85% and 3.30% respectively year on year, while the volume of main routes has slowed down, registering an increase of 1.18% (for 2014 the y.o.y. increase was 3.87%). Asian and European routes showed the worst performance with negative growth of -1.35%. Overall, due to the supply-demand imbalance, the profits of shipping companies vanished once again.

2.3.2 Dry Bulk Market

According to the annual report of Shanghai International Shipping Institute for the year 2015-2016, the year-round BDI in 2015 stood at 718 points on average, decreased by 35% compared with 2014 and hit a 30-year low. On February 18th, 2015, the BDI fell to a new low of 508 points.

Average BDI in 1985-2015

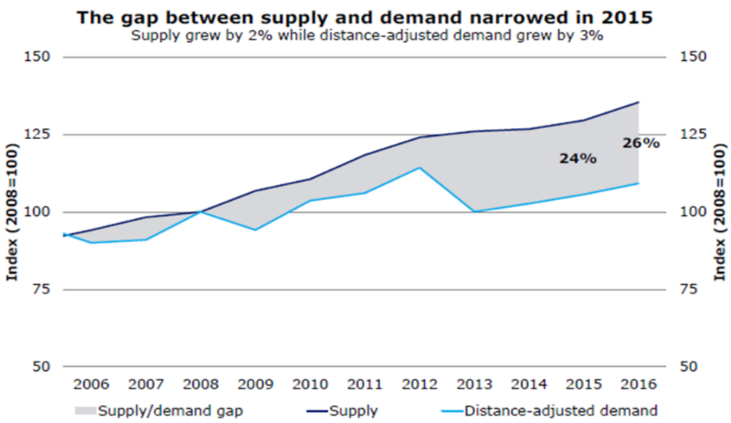


Data Source: *Baltic Exchange, prepared by Shanghai International Shipping Institute*

The global dry bulk cargo transportation capacity still surpass the demand growth, although the increased amount of demolitions and the reduced deliveries. As of December 2015, global dry bulk transportation amounted to 777 mill DWT and totaled 10.689 fleets in number. According to market surveys, about 90% fleets are slowing down their speed to offset the excess capacity. Meanwhile, the orders for new dry bulk carriers jumped from 699 (in 2014) to 241 (in 2015). Many shipowners of handling orders began to change their orders from bulk carriers to oil tankers or container ships to avoid the insufficient demand and the continuous depression of dry bulk market.

2.3.3 Tanker Market

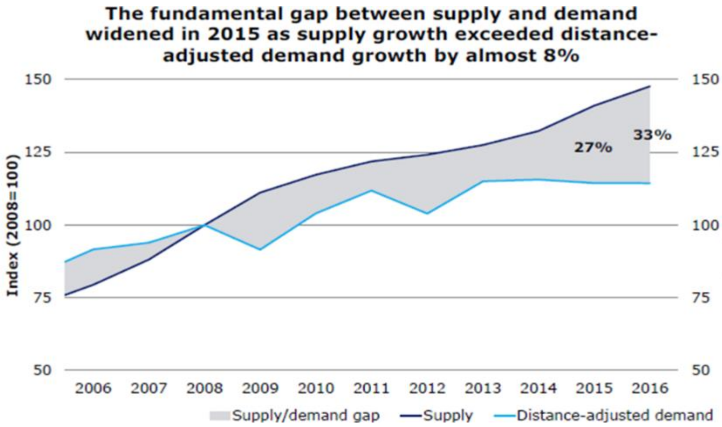
According to Danish Shipping Finance review and outlook as per May 2016, Crude Tanker Earnings are relatively high due to the drop in crude oil prices and reached their highest levels in 2015 since the financial crisis of 2008. This market has benefited from both strong demand growth and the low inflow of new vessels. In 2015, 9.3 million DWT were delivered, while only two VLCCs and three Aframaxes were demolished. This leads to a fleet growth supply of 2%. On the other hand, distance-adjusted demand grew by 3% which narrowed the gap between supply and demand.



Data Source: *IHS Global Insight, Danish Ship Finance*

New contracts for carriage of goods reached their second-highest level ever in 2015. 35.8 million DWT in total was contracted during this year. Hopefully, if this trend continues, there may be a reduction in the nominal supply surplus.

As it concerns the Clean Tanker Market, its earnings have suffered a significant decline as they can be measured by Clarksons' 'Average Clean Products Earnings'. According to Danish Shipping Finance, the average earnings were more than USD 28.000 per day in July 2015 and dropped to almost USD 14.000 per day in March 2016. For the year 2015, the product tanker fleet grew by 6% and the demolition market suffered a decrease to a historically low level. Only 24 vessels with a total capacity of 0.8 million DWT were scrapped during last year. Despite the high freight rates of 2015 though, 22% of the new orders that should be delivered during that year were postponed, and more than 12% were canceled. Finally, the nominal gap between supply and demand seems to have widened last year. It appears that demand for seaborne petroleum products contracted by 1% in 2015 compared with fleet growth of 6%. The estimated gap between supply and demand widened to 27% during 2015 as it is indicated by the following graph.



Data Source: *IHS Global Insight, Clarksons, Danish Ship Finance*

III. Data Collection & Analysis

3.1 Data Collection

This section defines the data used to conduct this study. The primary source of information was Clarkson's Shipping Intelligence Network, which collects and maintains an extensive number of data on the shipping industry. The selected sample is the CCFI (China Containerized Freight Index) and its trading lines which is promoted by the Ministry of Communications of PRC and developed by Shanghai Shipping Exchange, BDI (Baltic Dry Index), Baltic Clean Tanker Index (BCTI) and Baltic Dry Tanker Index (BDTI) which are provided by the London-based Baltic Exchange.

The CCFI reflects the spot rates of China (export) container transport market and it is calculated from the weighted average of the 14 most common individual shipping lines which depart from China and arrive at Europe, Mediterranean, Japan, Korea, New Zealand, etc. According to Shanghai Shipping Exchange, CCFI is deemed as the second world freight index following the Baltic Dry Bulk Freight Index. The collection of freight information is being held by 22 domestic and foreign shipping companies[9] with high international prestige and significant market shares. Publication day is every Friday.

The raw dataset consists of weekly prices of the comprehensive index CCFI and 10[10] shipping lines that were chosen as a sample and covers the period from March 2003 to May 2016. (670 observations per shipping route). **Appendix 1** plots the prices and the log-returns of each shipping line.

The Baltic Dry Index (BDI)[11] is a shipping and trade index that measures changes in the cost of transport of raw materials[12]. It is a composite of four sub-indexes of dry bulk carriers, Capesize (BCI), Supramax (BSI), Panamax (BPI) and Handysize (BHSI). These sub-indexes have been created according to the vessel's size. Finally, the BDI is released every day by the Baltic Exchange.

The raw dataset consists of weekly prices of the BDI that covers the period from March 2003 to May 2016. **Appendix 2** plots the prices and the log-returns of the index.

9 Among others COSCO, Maersk, Container Lines, Korea Marine transport, MSC, Sinotrans Container Lines, Evergreen Marine Corp. etc.

10 Ten out of fourteen shipping lines were chosen as a sample, due to lack of data for the other shipping lines.

11 The BDI is the successor of the Baltic Freight Index and was brought into operation on 1 November 1999.

12 Such as iron-ore, coal, gain etc.

Finally, the Baltic International Tanker Routes comprised of Baltic Dirty Tanker Index (BDTI) and Baltic Clean Tanker Index (BCTI). The BCTI consists of 7 main shipping routes and is a benchmark price index for the worldwide shipping of oil products such as gasoline, diesel, etc. The BDTI consists of 18 main shipping routes for four classes of ships. (VLCC, Suezmax, Aframax and Panamax) It is a benchmark price index for tankers carrying mostly crude oil as cargo and these prices are quoted in the Worldscale system. The raw dataset consists of weekly prices of BCTI and BDTI from March 2003 to May 2016. **Appendix 2** plots the prices and the log-returns of the index.

3.2 Data Processing for CCFI

3.2.1 Testing for unit root

Before starting any quantitative analysis, we must ensure that our data is stationary. Augmented Dickey-Fuller test with a trend and an intercept was applied to test for a unit root in variables. The results are presented in **Table 3.1:**

Table 3.1 *ADF test for stationarity on levels, LogLevels and Logreturns for CCFI and its routes.*

	Level		LNPrice		Logreturns	
	t-Statistics	p-value	t-Statistics	p-value	t-Statistics	p-value
Composite Index(CCFI)	-1,44	0,56	-0,99	0,76	-13,47	0,00***
Japan	-5,00	0,00***	-4,63	0,00***	-27,43	0,00***
Europe	-2,98	0,14	-2,25	0,46	-18,24	0,00***
WC North America	-0,43	0,90	-0,22	0,93	-31,57	0,00***
EC North America	-1,55	0,51	-0,76	0,83	-30,80	0,00***
Hong Kong	-1,74	0,41	-1,89	0,33	-21,47	0,00***
Korea	-3,33	0,00***	-3,14	0,02**	-25,58	0,00***
Southeast Asia	-1,57	0,50	-1,60	0,48	-13,42	0,00***
Mediterranean	-2,92	0,04**	-2,86	0,04**	-9,96	0,00***
South America	-1,35	0,61	-0,73	0,84	-29,05	0,00***
W/E Africa	-1,41	0,58	-0,99	0,76	-35,29	0,00***
Test critical Values	**1% level**	-3,44				
	5% level	-2,87				
	10% level	-2,57				

All time series can be considered stationary in log returns. Korea and Mediterranean can be considered stationary on levels for a=5% (**) and Japan for a=1%(***).

The results in **Table 3.1** indicate that log-levels of most variables are non-stationary, while their log-first differences are stationary. This suggests that all variables are in fact integrated of order 1 or I(1). The exceptions are the price of Korea, Japan and

Mediterranean lines which are stationary I(0). As concluded the data that will be used for the rest of the thesis is the log returns of each series.

3.2.2 Descriptive Statistics

A brief descriptive statistics based on log-returns of the time series of CCFI, is presented below:

Table 3.2 *Descriptive Statistics for the log returns of CCFI and its trading lines*

	Composite Index(CCFI)	Japan	Europe	WC North America	EC North America	Hong Kong
Mean	-0,00062	-0,000166	-0,001066	-0,000824	-0,000541	0,000164
Median	-0,001404	-0,002054	-0,00155	-0,001453	-0,001524	-0,0006
Maximum	0,062064	0,238492	0,200431	0,165591	0,113825	0,215428
Minimum	-0,051607	-0,192379	-0,098585	-0,155618	-0,139477	-0,224192
Std. Dev.	0,015624	0,040256	0,028953	0,027118	0,024488	0,049838
Skewness	0,466978	0,437735	1,226636	0,098248	-0,022048	0,040446
Kurtosis	4,712573	9,701372	9,872821	10,73398	8,117826	5,963118
Jarque-Bera	104,8015	1257,961	1466,71	1648,452	721,4288	241,9979
Probability	0,00	0,00	0,00	0,00	0,00	0,00
	Korea	**Southeast Asia**	**Med/nean**	**W/E Africa**	**South America**	
Mean	-0,000154	-0,000119	-0,001034	-0,000989	-0,001214	
Median	-0,000106654	-0,000357	-0,001757	-0,001179	-0,001375	
Maximum	0,189687	0,170128	0,252709	0,403876	0,252095	
Minimum	-0,212047	-0,154002	-0,188375	-0,330454	-0,272101	
Std. Dev.	0,045216	0,035162	0,041329	0,048048	0,044806	
Skewness	0,055447	0,09437	0,806536	0,432208	0,157538	
Kurtosis	6,094664	5,244802	9,753042	15,75305	9,030518	
Jarque-Bera	264,1037	139,7673	1327,662	4499,964	1004,346	
Probability	0,00	0,00	0,00	0,00	0,00	

Summarizing our data in that way, we can obtain useful and meaningful information in order to proceed to the quantitative analysis. Measures of central tendency (e.g. mean, median) describe the center of a dataset. For the CCFI and its trading lines, all the variables except from the shipping line of Hong Kong seem to have an average negative return through the estimation period. In this table are also mentioned the minimum and the maximum values of the CCFI and the individual routes. It is noticeable that W/E Africa, S. America and Mediterranean routes have maximum values of more than 25%, while the first two have a minimum value of more than -25%. Again, the two routes mentioned above seem to have the highest standard deviation. Skewness, positively or negatively, measures the asymmetry of the variable from the mean. Skewness equals to zero, means that data are perfectly symmetrical. In our case, most of the indices are positively skewed which indicates that the most values are concentrated on the left side of the mean. The kurtosis of any normal distribution is 3, distribution with kurtosis less than 3 is said to be platykurtic and more than 3 leptokurtic. In our sample, all variables seem to have fat tails peaked kurtosis which is a common feature of financial time series. A fat-tailed distribution looks normal, but the parts far away from the average are thicker, meaning a higher chance of huge deviations. Finally, Jarque-Bera test for normality confirms that all the variables seem to reject the null hypothesis for normality.

3.3 Data Processing for CCFI, BDI, BCTI and BDTI

3.3.1 Testing for unit root

Again, Augmented Dickey Fuller test with a trend and an intercept was applied in order to test for a unit root in variables. Results are presented in **Table 3.3:**

Table 3.3 *ADF test for stationarity on levels, LogLevel and Logreturns for the BDI, BCTI and BDTI.*

	Level		LogLevels		Logreturns	
	t-Statistics	**p-value**	**t-Statistics**	**p-value**	**t-Statistics**	**p-value**
China Containerized Freight Index(CCFI)	-1,44	0,56	-0,99	0,75	-13,46	0,000***
Baltic Dry Index (BDI)	-2,24	0,18	-1,62	0,46	-11,48	0,000***
Baltic Clean Tanker Index (BCTI)	-5,45	0,00***	-5,31	0,00***	-14,29	0,000***
Baltic Dirty Tanker Index (BDTI)	-4,11	0,00***	-3,3	0,02**	-16,99	0,000***
Test critical Values	**1% level**	-3,97				
	5% level	-3,41				
	10% level	-3,13				

*All time series can be considered stationary in log returns. ***, **,* indicates stationarity for 1%, 5% and 10% respectively.*

The results in **Table 3.3** indicate that the log-first differences are stationary. As concluded the data that will be used for the rest of the thesis is the log returns of each series.

3.3.2 Descriptive Statistics

A brief descriptive statistics based on natural logarithms of the time series of BDI, BCTI, BDTI and CCFI is presented below in **Table 3.4**:

Table 3.4 *Descriptive Statistics for the log returns of BDI, BCTI, BDTI and CCFI.*

	Baltic Dry Index (BDI)	Baltic Clean Tanker Index (BCTI)	Baltic Dirty Tanker Index (BDTI)	China Containerized Freight Index (CCFI)
Mean	-0,001621	-0,001454	-0,001625	-0,0006
Median	0,00258	-0,005907	-0,001315	-0,0014
Maximum	0,373789	0,302029	0,275462	0,062
Minimum	-0,473861	-0,297664	-0,386039	-0,051
Std. Dev.	0,080028	0,051198	0,070968	0,015
Skewness	-0,356286	0,546717	0,016857	0,46
Kurtosis	6,280595	7,784482	5,626219	4,71
Jarque-Bera	319,31	682,46	195,44	104,8
Probability	0,00	0,00	0,00	0,00

Again, all the indices tend to have slightly negative average returns through the estimation period. Surprisingly, the maximum values range from 27.5% to 37.3% and the minimum values range from -29.7% to -47.3%. At a first glance, CCFI seems to perform the lowest volatility as its returns fluctuate from -5.1% to 6.2%. Again, all time series are leptokurtic.

IV. Empirical Methodology

4.1 Time series definition

A time series is a sequence of numbers, occurring in equal uniform intervals. If a time series can be predicted, it is said to be **deterministic**. Most of time series are **stochastic**, and that means that future values are only partly determined by knowledge of past values. Stochastic processes are often used for modeling time series data and is said that are completely random if their mean is equal to zero and their variance is equal to σ^2 and it is not correlated over time. (Gujarati, 2003).He also suggests that the best prediction of the price of an asset tomorrow is equal to its price today plus a purely random shock which is called **the random walk phenomenon.**

4.2 Time Series Theory

Given a daily price process at trading day t, P_t, we define the compounded daily returns by

$$r_t = log\frac{P_t}{P_{t-1}} \quad t = 1, \dots, n$$

The conditional density of r_t is denoted by $f\ (r_t|F_{t-1})$ where F_{t-1} is the conditional distribution which is determined as $F(r_t|r_{t-1}, \dots, r_{t-N})$. An assumption made in financial study is that the returns $\{r_t|t = 1, \dots, T\}$ are independently and identically distributed $(i.i.d)$ as normal with fixed mean and variance.

A time series $\{\boldsymbol{Y_t}\}$ is called strictly stationary if the random vectors $(Y_{t1}, \dots, Y_{th})^T$, $(Y_{t1}, \dots, Y_{th})^T$ and $(Y_{t1+h}, \dots, Y_{tn+h}t)^T$ have the same joint distribution for all sets of indices $\{t_1, \dots, t_n\}$ and for all integers $t, h > 0$. However, strict stationarity is rarely satisfied and a weaker definition of *second order* or *weak* stationarity is usually used. A time-series is called *weakly stationary* if, for all $h, t \in Z$:

$$E(Y_t) = \mu$$

$$Cov(Y_t, Y_{t+h}) = \gamma_h$$

(by letting $h = 0$ it implies that the variance is constant)

In the condition of weak stationarity, it is assumed that the first two moments of Y_t are finite. Before applying any conventional method of time series, it is completely necessary to ensure that the mean and the variance remain stable over time. Granger and Newbold (1974) introduced the notion of spurious regression which explains regressions with high R^2 but with extremely low value for DW statistic when our data is non-stationary. The graph of a stationary series varies randomly around a constant mean (called **mean reversion**) and also its variance will be constant through time. Consider the simplest autoregressive model $AR(1)$ that has been frequently used to characterize stationary time series:

$$y_t = a_1 y_{t-1} + u_t , \qquad t = 1,2,3, \dots h \quad |a_1| < 1$$ [13]

4.3 Univariate time series analysis

First-moment modelling is not the primary focus of this thesis. However, a reasonable model for the first moment has to be used. A misspecification in this equation could lead to wrong conclusions about which $GARCH$ model to support.

Box and Jenkins (1976) proposed a three-step procedure for modeling time series data which is going to be followed at this first part:

1. **Identification:** At that stage, an initial consideration of a class of $ARMA$ models is made according to graphical methods (such as ACF and $PACF$) that will later be tested for their validity.
2. **Estimation:** At that stage, simple least squares is applied to the appropriate $ARMA$ model in order to estimate the parameters of the AR and MA terms.
3. **Diagnostic Checking:** Finally, it is decided whether the model is adequate and fits the data reasonably well. Diagnostic checks, such as residual analysis or fitting extra (or less) parameters are performed.

- ***The Autoregressive process –AR(p)***

The *Autoregressive model*- $AR(p)$ was firstly introduced by Yule in 1926 and has the following form:

$$AR(p): \quad Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \cdots + \alpha_p Y_{t-p} + u_t$$

That means that Y at time t depends on its value in the previous p time periods plus a random shock (or disturbance) at time t.

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13 Denote that when α=1 the process is stationary and is called ‘’random walk”, and when α=0 the process is called “white noise”.

- ***The Moving Average process- MA(q)***

The *Moving Average* model of order q was introduced in 1937 by Slutsky and has the following form:

$$MA(q): \quad Y_t = \mu + \beta_0 u_t + \beta_1 u_{t-1} + \beta_2 u_{t-2} + \cdots + \beta_q u_{t-q}$$

In short, the moving average process is simply a linear combination of white noise error terms. Wold (1938) proved that a stationary series that is purely stochastic can always be decomposed into one deterministic process and one other being a moving average process. This representation is widely known as Wold's decomposition theorem.

- ***The Autoregressive and Moving Average process – ARMA (p,q)***

Obviously, it is likely that Y has both characteristics of AR and MA components and is, therefore, $ARMA$. This process has the following form:

$$ARMA(p,q): \quad Yt = \theta + \alpha_1 Y_{t-1} + \cdots + \alpha_p Y_{t-p} + \beta_0 u_t + \ldots + \beta_q u_{t-q} + e_t$$

- ***Integrated stochastic process***

If a non-stationary series, y_t must be differenced d times before it becomes stationary, it is said to be integrated of order d. It is symbolized by $y_t \sim I(d)$, and so, if $y_t \sim I(d)$ then $\Delta^d y_t \sim I(0)$. An $I(0)$ series is stationary, whereas an $I(1)$ contains one unit root and so on.

Therefore, we can rewrite the equation of an $ARMA(1,1)$ model as:

$$(1-L)Y_t = \theta + \psi y_{t-1} + \alpha(1-L)y_{t-i} + \beta u_{t-1} + u_t$$

Where L is the lag operator and $(1-L)$ is the first difference. This equation is called $ARIMA(1,1,1)$.

4.4 Time Series models for volatility modelling-Conditional variance

Since the early decades of the twentieth century, asset returns had been assumed to form an i.i.d. process with zero mean and constant variance. However, in real economic and financial series data, the assumptions of normality, independence and homoscedasticity do not always hold. Firstly Mandelbrot (1963) and Fama (1965) and later many others argued that after a big rise (fall) in prices, a big rise (fall) in prices is also observed. This behavior is known as *volatility clustering* and implies that volatility shocks today will influence the expected volatility some periods later. Again, Mandelbrot (1963) was the first that noticed that asset returns are highly leptokurtic and slightly asymmetric. This phenomenon is apparent when asset returns are plotted. Finally, Black (1976) firstly noted the so-called *leverage effect* which refers to the tendency for changes in asset's volatility to be negatively correlated with changes in asset's price. According to Cont (2001), there are many other non-trivial statistical properties that asset prices share such as conditional and unconditional heavy tails, volume/volatility correlation, non-trading period effects, etc. All above empirical observations suggest that the financial returns exhibit heteroskedasticity and even the volatility depends on the volatility observed in the immediately former periods. The GARCH-family models offer a solution to these problems and tend to treat heteroskedasticity as a variance to be modeled.

- ***Autoregressive Conditional heteroskedasticity model- ARCH (q)***

This concept was firstly introduced by Engle (1982). He models the discrete returns of a process as:

$$r_t = \mu_t + u_t$$

where μ_t is the mean return and $u_t = Z_t \, \sigma_t$ where Z_t iid with $E[Z_t] = 0$ and $Var[Z_t] = 1$

The ARCH model and its extensions (GARCH, TARCH, E-GARCH, etc.) are among the most successful models for modelling the conditional variance. The ARCH model with q parameters can be defined as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \ldots + \alpha_q ut_{t-q}^2$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} (\alpha_i \, u_{t-i}^2)$$

With $\alpha_j \geq 0$ for conditional variance to be possitive and $\sum_{j=1}^{q} \alpha_j < 1$ for covariance stationarity. Denote that if the the process is covariance stationary, its unconditional variance is equal to $\sigma^2 = \alpha_0 \left(1 - \sum_{j=1}^{q} (\alpha_j)\right)^{-1}$.

Under this model, the autocorrelation in volatility is modelled by allowing the conditional variance of the error term (σ_t^2), to depend on q lagged squared errors and can capture the volatility clustering.

According to Xekalaki and Degiannakis (2010), the conditional and the unconditional mean as well as the unconditional variance of the returns remain constant, while the conditional variance has a time-varying character.

In empirical applications, it is not rare to observe a relatively long lag ARCH model and to avoid the bias of the parameters' restrictions, the GARCH model is formulated.

- ***Generalized Autoregressive Conditional heteroskedasticity model - GARCH(p,q)***

The $GARCH$ model was developed by Bollerslev (1986) and is more widely used as it avoids overfitting and it is more parsimonious. The $GARCH(p, q)$ allows the current conditional variance to depend upon p lags of the conditional variance and q lags of the squared errors. It can be expressed as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} (\alpha_i \, u_{t-i}^2) + \sum_{j=1}^{p} \beta_j \, \sigma_{t-j}^2$$

where $\alpha i \geq 0$, $\beta j \geq 0$ for non-negativity of the variance and $\left(\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j \right) < 1$ for stationarity of variance. The sum mentioned above measures the persistence of variance. This model can capture thick tailed returns and volatility clustering. Moreover, it is assumed that the impact of news on the conditional volatility depends only on the magnitude of the innovation and not of the sign. For that reason, the two following models are introduced.

➢ ***The Exponential GARCH model- E-GARCH (p,q)***

The asymmetric $E - GARCH$ model, which introduced by Nelson (1991), specifies conditional variance in logarithmic form, which means that there is no need to impose restrictions in order to avoid negative variance. It can be expressed as:

$$ln\,\sigma_{j,t}^2 \;=\; \omega_j \;+ \beta_j \ln\left(\,\sigma_{j,t-1}^2\right) + \;\gamma\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + a\;\left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \;\sqrt{\frac{2}{\pi}}\right]$$

For an E-GARCH model, $\sigma_{j,t}^2$ depends on both the magnitude and the sign of ε_t. The coefficient α represents the magnitude effect of the model, the $GARCH$ effect. The coefficient β measures the persistence in conditional volatility irrespective of anything happening in the market. When β is large, then volatility takes a long time to die out . The E-GARCH process is covariance stationary if $\sum_{j=1}^{q} \beta_j < 1$.

The coefficient γ measures the asymmetry (the leverage effect), the parameter of importance so that the $EGARCH$ model allows for testing of asymmetries. If γ is equal to zero the model is symmetric. If $\gamma < 0$ the positive shocks generate less volatility than negative shocks.

The unconditional variance (long term variance) of the $EGARCH$ (1,1) model is assumed constant and is presented below. If unconditional variance is relatively large then long term variance in the market is relatively high.

$$\bar{\sigma}^2 = \exp\left(\frac{\omega}{1-\beta}\right)$$

➢ ***Threshold GARCH Model- T-GARCH (p,q)***

The asymmetric $T - GARCH$ model proposed by Zakoian (1994) captures the threshold effect in expected volatility. That means that large shocks are less persistent in volatility than small shocks. A $T - GARCH$ (1,1) model can be defined as:

$$\sigma_t \;=\; a_0 \;+\; a_1|\varepsilon_{t-1}| \;+\; a_2|\varepsilon_{t-1}|I\;(\varepsilon_{t-1} \;< 0) \;+\; \beta\sigma_{t-1}$$

Denote that this model parameterizes the conditional standard deviation.

➢ ***Distributions***

A feature of ARCH process is that even if the conditional distribution of the innovation is normal, the unconditional distribution has thicker tails. Thus, there is evidence that the conditional distribution of ε_i is non-normal, as well. In this thesis, three different probability distributions are used. The Standard Normal distribution (Gaussian), the Student-t and the Generalized Error Distribution (GED). For the estimation of the parameters the log-likelihood functions of these distributions are used.

4.5 Practical Issues for Model building

➢ ***Auto-correlation function***

One test of stationarity is based on the autocorrelation function which helps to measure the temporal connections between different components of the series Y_t, in fact:

$$\hat{\rho}_h = \frac{cov(Y_t, Y_{t+h})}{\sigma Y_t \sigma Y_{t+h}} = \frac{\hat{\gamma}_h}{\sqrt{\gamma_0 \gamma_0}} = \frac{\hat{\gamma}_h}{\hat{\gamma}_0}$$

A plot of $\hat{\rho}_h$ against h is known as the sample correlogram. For a probably stationary time series, the autocorrelation at various lags hovers around zero and for a non-stationary, the autocorelation coefficients are quite high.

➢ ***Partial autocorrelation function***

The partial autocorrelation function, (PACF) measures the correlation between an observation h periods ago and the current observation, after removing the linear effect of observations of intermediate lags (for example all lags$< h$). At lag 1 the ACF and PACF are equal since there are no intermediate lag effects. If ρ_{12}, ρ_{23}, ρ_{13} are the correlation coefficients between the variables Y_t (taken pairwise) then, the partial correlation between $Y1, Y2$, when $Y3$ is kept fixed is:

$$\rho 12.3 = \frac{\rho_{12} - \rho_{23} - \rho_{13}}{\sqrt{(1-\rho_{13}^2)(1-\rho_{23}^2)}}$$

The *ACF* and the *PACF* plots suggest a possible $\boldsymbol{ARMA}\,(\boldsymbol{p}, \boldsymbol{q})$ model for this data. Finally, the AR process has its ACF tailing off and PACF cutting off, and MA process has its ACF cutting off and PACF tailing off.

- ***Information Criteria***

An important issue regarding the model building is the determination of orders of AR and MA terms as well as the $ARCH$ and $GARCH$ terms. Two widely measures goodness of fit are Akaike (1974) Information criterion (AIC) and Schwarz (1978) information criterion (SIC). They measure the trade-off between model fit and complexity of the model. Their algebraic expressions are:

$$AIC = -2ln(L) + 2p$$

$$SIC = -2ln(L) + ln(N)p$$

where L is the value of the likelihood function evaluated at the parameter estimates, N is the number of observations and p is the number of estimated parameters. A lower AIC or SIC indicates a better fit model (more parsimonious). However, in this thesis, only SIC will be used because it penalizes the number of parameters stronger than does AIC.

4.6 Empirical tests

- ***Test for Stationarity or Unit root test***

Tests for stationarity firstly proposed from Dickey and Fuller (1979), Philips and Perron (1988), Kwiatkowski–Phillips–Schmidt–Shin (1992), etc. For the purpose of this study, the latest version of Dickey- Fuller test will be used, now referred as Augmented Dickey-Fuller test (ADF). Test is performed by running a least squares regression of the form:

$$\Delta y_t = \psi y_{t-1} + \sum_{i=1}^{p} a_i \, \Delta y_{t-i} + u_t$$

The null hypothesis for this test is whether $\psi = 0$ versus the alternative $\psi < 0$. If H_0 is rejected we conclude that y_t does not contain a unit root and our data are stationary. The test statistics for the original DF test is defined as:

$$Test\ statistics = \hat{\psi} \,/\, SE(\hat{\psi})$$

The number of lags used in the ADF test is decided by AIC and SIC.

- ***Autocorrelation Tests***

With this test, we want to see whether there is a pattern in residuals from the estimated model.

1. Box-Pierce test

Box and Pierce (1970) proposed the portmanteau statistic to test the joint hypothesis that the ρ_h are simultaneously equal to zero(is testing for high order serial correlation). The Q statistic is defined as:

$$Q = n \sum_{h=1}^{m} \widehat{\rho_k}^2$$

where m is the lag-length and n is the sample size. If computed Q is greater than the critical Q value from the chi-square distribution, we can reject the null hypothesis that all ρ_k are zero.

2. Ljung and Box test

Ljung and Box (1978), modify the Q statistic to increase the power of the test in finite samples as follows:

$$Q = T\,(T+2) \sum_{h=1}^{m} \frac{\hat{\rho}_h^2}{T-h}$$

where $Q \sim \chi^2_{h-q-p}$. Again, we reject the null hypothesis that autocorrelations up to h are zero if Q is greater than the appropriate critical value.

According to Tsay (2005), the Ljung-Box statistics is recommended to check the serial correlation of residuals as it tests the serial dependence at higher order lags instead of DW test.

- ***Heteroscedasticity Test***

If errors do not have a constant variance, it is said that they are heteroscedastic which can be detected either by graphical methods or with formal tests. Engle (1982) proposed the Lagrange Multiplier test (LM) in order to test for $ARCH$ effects in the residuals. The test statistics is defined as TR^2, where T is the number of observations and R is the multiple correlation coefficient computed from the regression of squared residuals on a constant and on q own lags as it appears bellow:

$$\sigma_t^2 \ = \alpha_0 + \alpha_1 u_{t-1}^2 \ + \alpha_2 u_{t-2}^2 \ + \ ... + \alpha_p u_{t-p}^2$$

The null and the alternative hypothesis are:

H_0 : α_1 =0 and α_2 =0 and … and α_p=0 (there is no $ARCH$ effect)

H_1 : $\alpha_1 \neq 0$ and $\alpha_2 \neq 0$ and … and $\alpha_p \neq 0$

The test is asymptotically distributed as a $\chi^2(q)$. Ignoring the $ARCH$ effects may result in loss of efficiency.

- ***Normality tests***

1. Jarque-Bera test

JB test, proposed by Carlos Jarque and Anil Bera, is a goodness of fit test that measures the departure from normality. In other words, it tests whether our sample has the kurtosis and the skewness of a normal distribution. The test statistics is defined as:

$$JB \ = \frac{n-k-1}{6}(S^2 \ + \frac{1}{4}(C - 3)^2)$$

where n are the degrees of freedom, k is the number of regression parameters, S is the sample skewness and C is the sample kurtosis.

JB test has an asymptotic chi-square distribution.

V. Empirical Results

5.1 Empirical Results for the China Containerized Freight Index (CCFI)

5.1.1 Procedure for model selection- the mean equation

Autocorrelation and partial autocorrelation functions are presented in **Appendix 3** which suggest possible ARMA models for modeling the mean equation. After identifying the possible combinations, and based solely on the information criterion SIC, various ARMA (p,q) models were fitted to the daily returns of the CCFI and its trading lines. The results, according to the lowest value of SIC, are presented in **Table 5.1:**

Table 5.1. *ARMA selection according to SIC for the CCFI*

Composite Index (CCFI)	**ARMA(1,1)**	Korea	**ARMA(2,3)**
Japan	**ARMA(1,1)**	South/East Asia	**ARMA(0,2)**
Europe	**ARMA(1,1)**	Meditterranean	**ARMA(2,4)**
North America West Coast	**ARMA(2,0)**	West/East Africa	**ARMA(1,2)**
North America East Coast	**ARMA(1,0)**	South America	**ARMA(1,0)**
Hong-Kong	**ARMA(0,1)**		

5.1.2 Procedure for model selection- the variance equation

Once the ARMA specification has been determined, joint specifications of the conditional mean and the conditional variance of the series take place. According to Weiss (1984) and Bollerslev (1986), the identification of the correct ARCH model can be achieved by examining the ACF of the squared residuals of the estimated ARMA model. (See **Appendix 4**) The ACF and PACF of squared residuals show persistent correlation which indicates ARCH processes present in all series. In addition, the residuals of the ARMA models developed above were tested through the ARCH-LM test to confirm formally that heteroscedasticity exists.

Therefore, several ARMA-GARCH[14] models were estimated, and the most suitable were chosen according to the SIC. In addition, E-GARCH (1,1) and T-GARCH (1,1) models were computed to check whether there is asymmetry in the volatility.

14 ARCH(q), q=1,2.3,4, GARCH(p,q) p,q $\in$ [0,2]

Sometimes, normal (Gaussian) distribution cannot always be assumed due to the nature of financial data. For that reason, the fat-tailed Student-t and the GED[15] (Generalized Error Distribution) are commonly used as they are believed to capture the leptokurtic characteristics better. In this thesis, the results of all distributions will be presented. The changes on the distribution assumption and the joint specification of the ARMA-GARCH model had influenced the significance of several terms in the mean equations presented above and so, a further adjustment should be performed. "*For instance, if some of the estimated AR and MA coefficients are not significantly different from zero, then the model should be simplified by trying to remove those parameters. On the other hand, if residual autocorrelation function shows additional serial correlations, then the model should be extended to take care of those correlations*" (Tsay,2005). The results are presented in **Appendix 5**. The fitted model examined carefully to check for possible model inadequacies. If a fitted model was found to be inadequate, it was refined. The outputs of each estimated model for the eleven individual routes are presented in **Table 5.2** to **Table 5.12.**

15 The GED is a symmetric distribution that can be both platykurtic and leptokurtic depending on the degree of freedom.

Table 5.2: *Output for ARMA (1,2)-GARCH(1,1) model for the composite index CCFI*

Dependent Variable CCFI *GARCH(1,1) estimation with Student's distribution*				
Variable	**Estimated Coefficient**	**Standard Error**	**z-statistic**	**P-value**
C	-0.001119	0.000881	-1.269820	0.2041
AR(1)	0.763812	0.065356	11.68691	0.0000
MA(1)	-0.675173	0.072645	-9.294027	0.0000
MA(2)	0.128095	0.047555	2.693623	0.0071
Variance Equation				
Alpha0	3.84E-05	1.28E-05	2.989441	0.0028
Alpha1	0.290449	0.079409	3.657618	0.0003
Beta1	0.573118	0.089213	6.424179	0.0000
T-DIST DOF	5.445823	1.278994	4.257894	0.0000
Se	0,014982			
RBS	0.081719			
DW	1.898332			
LL	1896.550			
SIC	-5.668427			
LjBQ(10)	3.7268	(0.811)		
LjBQS(10)	4.6916	(0.698)		
SK(eh)	0.355970			
KU(eh)	5.313860			
ARCH TEST F-STATISTIC	0.124138	(0.724)		

Table 5.3: *Output for ARMA (1,1)-GARCH(1,2) model for the trading line of Japan*

Dependent Variable Japan *GARCH(1,2) estimation with GED*				
Variable	**Estimated Coefficient**	**Standard Error**	**z-statistic**	**P-value**
C	-0.001654	0.000719	-2.299311	0.0215
AR(1)	-0.871129	0.094553	-9.213168	0.0000
MA(1)	0.833658	0.109073	7.643138	0.0000
Variance Equation				
Alpha0	3.33E-06	2.08E-06	1.605867	0.1083
Alpha1	0.340040	0.101963	3.334923	0.0009
Alpha2	-0.301085[16]	0.099571	-3.023837	0.0025
Beta1	0.956930	0.013872	68.98477	0.0000
GED PARAMETER	1.141782	0.087368	13.06863	0.0000
Se	0.040220			
RBS	0.005429			
DW	2.02935			
LL	1431.943			
SIC	-4.222036			
LjBQ(10)	4.6770	(0.791)		
LjBQS(10)	8.7806	(0.361)		
SK(eh)	0.570282			
KU(eh)	4.971800			
ARCH TEST F-ST	0.478238	(0.4895)		

16 According to Xekalaki et al. (2010, p. 21) in a GARCH (1,2) model, the necessary conditions require that Alpha0 ≥0, 0 ≤beta1< 1, Alpha1≥0,and beta1*alpha1 + alpha2 ≥0 which is satisfied.

Table 5.4: *Output for ARMA (1,1)-EGARCH(1,1) model for the trading line of Europe*

Dependent Variable Europe EGARCH(1,1) estimation with Student-t				
Variable	**Estimated Coefficient**	**Standard Error**	**z-statistic**	**P-value**
C	-0.003177	0.001257	-2.526519	0.0115
AR(1)	0.816380	0.044949	18.16252	0.0000
MA(1)	-0.611845	0.061924	-9.880608	0.0000
Variance Equation				
C(1)	-0.238987	0.078359	-3.049915	0.0023
C(2)	0.206935	0.046447	4.455286	0.0000
C(3)	-0.101794	0.032948	-3.089545	0.0020
C(4)	0.985744	0.0081269	119.2134	0.0000
T-DIST. DOF	3.437380	0.482463	7.124654	0.0000
Se	0.027254			
RBS	0.115298			
DW	1.844127			
LL	1636.3083			
SIC	-4.879133			
LjBQ(10)	10.075	(0.260)		
LjBQS(10)	6.7437	(0.565)		
SK(eh)	2.026			
KU(eh)	21.17			
ARCH TEST F-STATISTIC	0.1997	(0.655)		

Table 5.5: *Output for ARMA(1,0)-GARCH(1,1) model for the trading line of WC America*

Dependent Variable WC N. America GARCH(1,1) estimation with Student-t				
Variable	**Estimated Coefficient**	**Standard Error**	**z-statistic**	**P-value**
C	-0.001032	0.000577	-1.788182	0.0737
AR(1)	-0.144869	0.043227	-3351358	0.0008
Variance Equation				
Alpha0	0.000155	4.11E-05	3.766265	0.0002
Alpha1	0.454537	0.127124	3.575542	0.0003
Beta1	0.371856	0.102897	3.613860	0.0003
T-DIST. DOF	3.936861	0.680354	5.786493	0.0000
Se	0.026599			
RBS	0.037080			
DW	2.071517			
LL	1620.803			
SIC	-4.852502			
LjBQ(10)	11.075	(0.271)		
LjBQS(10)	7.3717	(0.598)		
SK(eh)	0.009258			
KU (eh)	6.979041			
ARCH TEST F-STATISTIC	0,164989	(0.6847)		

Table 5.6: *Output for ARMA (2,1)-GARCH(1,1) model for the trading line of EC America*

Dependent Variable EC N. America GARCH(1,1) estimation with Student-t				
Variable	**Estimated Coefficient**	**Standard Error**	**z-statistic**	**P-value**
C	-0.001144	0.000915	-1.251262	0.2108
AR(1)	0.665358	0.097435	6.828765	0.0000
AR(2)	0.166411	0.038314	4.34333	0.0000
MA(1)	-0.748345	0.094858	-7.889085	0.0000
Variance Equation				
Alpha0	1.89E-05	9.64E-06	2.056283	0.0398
Alpha1	0.166257	0.049219	3.377930	0.0007
Beta1	0.831815	0.037293	22.30498	0.0000
T-DIST. DOF	3.489075	0.567430	6.148908	0.0000
Se	0.024315			
RBS	0.014909			
DW	2.189281			
LL	1634.759			
SIC	-4.875122			
LjBQ(10)	10.840	(0.146)		
LjBQS(10)	11.532	(0.117)		
SK(eh)	-0.000395			
KU (eh)	6.629145			
ARCH TEST F-STATISTIC	0.282979	(0.594)		

Table 5.7: *Output for ARMA(0,1)-GARCH(1,1) model for the trading line of Hong Kong*

Dependent Variable Hong-Kong GARCH(1,1) estimation with Student-t				
Variable	**Estimated Coefficient**	**Standard Error**	**z-statistic**	**P-value**
C	-0.000390	0.000525	-0.742793	0.4576
MA(1)	-0.543933	0.029968	-18.15029	0.0000
Variance Equation				
Alpha0	1.51E-07	2.42E-06	0.062549	0.9501
Alpha1	0.022173	0.009053	2.449229	0.0143
Beta1	0.974780	0.008699	112.0570	0.0000
T-DIST. DOF	7.001430	2.051765	3.412394	0.0006
Se	0.043035			
RBS	0.268146			
DW	2.131968			
LL	1273.743			
SIC	-3.749553			
LjBQ(10)	13.824	(0.129)		
LjBQS(10)	10.113	(0.341)		
SK(eh)	0.097523			
KU (eh)	4.182311			
ARCH TEST F-STATISTIC	2.575071	(0.1090)		

Table 5.8: *Output for ARMA(0,1)-GARCH(1,1) model for the trading line of Korea*

Dependent Variable Korea *GARCH(1,1) estimation with Student-t*				
Variable	**Estimated Coefficient**	**Standard Error**	**z-statistic**	**P-value**
C	-0.000239	0.000745	-0.321005	0.7482
MA(1)	-0.415745	0.038615	-10.76649	0.0000
Variance Equation				
Alpha0	0.000596	0.000172	3.469879	0.0005
Alpha1	0.307578	0.094884	3.241639	0.0012
Beta1	0.411341	0.116836	3.520661	0.0004
T-DIST. DOF	5.142551	1.008423	5.099599	0.0000
Se	0.042329			
RBS	0.144853			
DW	1.960495			
LL	1238.520			
SIC	-3.672142			
LjBQ(10)	6.9274	(0.645)		
LjBQS(10)	8.1461	(0.519)		
SK(eh)	-0.089725			
KU (eh)	5.941489			
ARCH TEST F-STATISTIC	0.356968	(0.5504)		

Table 5.9: *Output for ARMA(0,2)-GARCH(1,1) model for the trading line of SE Asia*

Dependent Variable SE Asia *GARCH(1,1) estimation with Normal Distribution*				
Variable	**Estimated Coefficient**	**Standard Error**	**z-statistic**	**P-value**
C	-0.000400	0.000638	-0.626029	0.5313
MA(1)	-0.539294	0.039145	-13.77689	0.0000
MA(2)	0.195551	0.038854	5.032919	0.0000
Variance Equation				
Alpha0	1.46E-05	9.37E-06	1.562432	0.1182
Alpha1	0.080783	0.018610	4.340865	0.0000
Beta1	0.904442	0.021236	42.58912	0.0000
Se	0.030005			
RBS	0.273955			
DW	2.093369			
LL	1439.828			
SIC	-4.246071			
LjBQ(10)	12.232	(0.141)		
LjBQS(10)	2.4272	(0.965)		
SK(eh)	0.063417			
KU (eh)	3.571864			
ARCH TEST F-STATISTIC	0.257188	(0.6122)		

Table 5.10: *Output for ARMA(1,1)-EGARCH(1,1) model for the trading line of Mediterranean*

Dependent Variable Mediterranean *E-GARCH(1,1) estimation with Student-t*				
Variable	**Estimated Coefficient**	**Standard Error**	**z-statistic**	**P-value**
C	-0.004462	0.001642	-2.717166	0.0066
AR(1)	0.806587	0.059272	13.60822	0.0000
MA(1)	-0.646493	0.078919	-8.191873	0.0000
Variance Equation				
C(1)	-0.240771	0.081540	-2.952794	0.0031
C(2)	0.235252	0.045395	5.195589	0.0000
C(3)	-0.110727	0.033425	-3.312723	0.0009
C(4)	0.982024	0.009629	102.6058	0.0000
T-DIST. DOF	4.034863	0.597019	6.758344	0.000
Se	0.040797			
RBS	0.023749			
DW	1.844070			
LL	1405.132			
SIC	-4.161089			
LjBQ(10)	7.1211	(0.310)		
LjBQS(10)	1.6272	(0.898)		
SK(eh)	1.525559			
KU (eh)	16.84989			
ARCH TEST F-STATISTIC	0.077979	(0.78)		

Table 5.11: *Output for ARMA(1,0)-EGARCH(1,1) model for the trading line of S.America*

Dependent Variable South America *EGARCH(1,1) estimation with Student-t*				
Variable	**Estimated Coefficient**	**Standard Error**	**z-statistic**	**P-value**
C	-0.001145	0.000919	-1.246420	0.2126
AR(1)	-0.205349	0.042236	-4.861936	0.0000
Variance Equation				
C(1)	-1.360793	0.307950	-4.418874	0.0000
C(2)	0.566369	0.096326	5.879688	0.0000
C(3)	-0.032737	0.056832	-0.576023	0.5646
C(4)	0.850912	0.041982	20.26865	0.0000
T-DIST. DOF	3.825930	0.563252	6.792568	0.0000
Se	0.044640			
RBS	0.002173			
DW	1.822147			
LL	1254.748			
SIC	-3.733410			
LjBQ(10)	2.0762	(0.990)		
LjBQS(10)	2.5723	(0.979)		
SK(eh)	-1.087618			
KU (eh)	11.21496			
ARCH TEST F-STATISTIC	0.227690	(0.633)		

Table 5.12: *Output for ARMA(1,0)-EGARCH(1,1) model for the trading line of W.E Africa*

Dependent Variable W/E Africa ***EGARCH(1,1) estimation with Student-t***				
Variable	**Estimated Coefficient**	**Standard Error**	**z-statistic**	**P-value**
C	-0.000891	0.000520	-1.714109	0.0865
AR(1)	-0.201572	0.030562	-6.595450	0.0000
Variance Equation				
C(1)	-0.197352	0.049638	-3.975806	0.0001
C(2)	0.318371	0.078501	4.055614	0.0001
C(3)	-0.071385	0.040726	-1.752782	0.0796
C(4)	0.996469	0.005976	166.6991	0.0000
T-DIST. DOF	2.536119	0.272173	9.318034	0.0000
Se	0.045950			
RBS	0.080811			
DW	2.165992			
LL	1386.012			
SIC	-4.131180			
LjBQ(10)	8.4415	(0.490)		
LjBQS(10)	1.5960	(0.996)		
SK(eh)	-1.946457			
KU (eh)	31.32184			
ARCH TEST F-STATISTIC	0.107868	(0.7427)		

5.1.3 Output analysis

As reported, when the residuals were examined for heteroscedasticity by ARCH-LM test, the test provided strong evidence for ARCH effects in the mean equation and therefore GARCH-family models were applied to deal with this problem. The models were estimated using the maximum likelihood method. The log likelihood function was maximized using Marquardt's numerical iterative algorithm to search for optimal parameters. **Table 5.13** summarizes the results.

Table 5.13: *Summary of the estimated models for the CCFI and its trading lines*

	Selected ARMA-GARCH Model	Distribution
Composite Index (CCFI)	ARMA(1,2)- GARCH(1,1)	Student's T
Korea	ARMA(0,1)-GARCH(1,1)	Student's T
North America West Coast	ARMA(1,0)- GARCH(1,1)	Student's T
North America East Coast	ARMA(2,1)- GARCH(1,1)	Student's T
Hong-Kong	ARMA(0,1)- GARCH(1,1)	Student's T
South/East Asia	ARMA(0,2)- GARCH(1,1)	Student's T
Japan	ARMA(1,1)- GARCH(1,2)	GED
Meditterranean	ARMA(1,1)-EGARCH(1,1)	Student's T
West/East Africa	ARMA(1,0)-EGARCH(1,1)	Student's T
South America	ARMA(1,0)-EGARCH(1,1)	Student's T
Europe	ARMA(1,1)- EGARCH(1,1)	Student's T

- ***GARCH(1,1) model***

The first category consists of the Composite Index, Korea, NAWC, NAEC, Hong Kong and Southeast Asia trading lines whose conditional variance can be modelled by GARCH (1,1). The coefficients *alpha0* (constant) *alpha1* (ARCH term) and *beta1* (GARCH term) are highly significant, and the non-negativity condition is satisfied. This indicates that lagged conditional variance and squared residuals have an impact on the conditional variance. In other words, the news from previous periods about volatility has explanatory power on current volatility. The sum of the persistence coefficients (Alpha1, Beta1) is less than one which is required for stationarity in variance. Misspecification tests indicate that despite the adoption of the Student-t distribution this formulation still suffers from skewness and excess kurtosis. Finally, the LjBox Q statistics of standardized residuals confirms that the mean equations of the models presented above are adequate. Both the LjBoxQ of the squared standardized residuals and the ARCH-LM test confirm that the variance equations are adequate too.

- ***GARCH(1,2) model***

The second category consists solely of Japan route which can be modelled by GARCH (1,2) model. Although *Alpha2* term is negative, the model is still adequate as it satisfies the conditions mentioned by Xekalaki and Degiannakis (2010). Finally, misspecification tests indicate that both the mean equation and the variance equation are adequate in describing the linear dependence in the return and volatility series.

- ***E-GARCH(1,1) model***

The third category consists of Europe, Mediterranean, South America and W/E Africa trading lines that can be modelled by the asymmetrical E-GARCH (1,1) model. The outputs indicate that all the coefficients are statistically significant except from the case of S. America where the coefficient of the asymmetric volatility response is not statistically different from zero. In the rest of the models, the parameter of the asymmetric volatility response (C(3)) is negative and significant indicating that positive shocks generate less volatility than negative shocks. In this model, no restrictions were set for the coefficients as it models the $ln\ \sigma^2_t$. The LjBox Q statistics indicates the absence of tenth-order serial correlation as well as the ARCH-LM test does not exhibit additional ARCH effects. The models seem to be adequate in describing the linear dependence in the return and volatility series.

5.1.4 Volatility Comparison Through Conditional Coefficient of Variation

After modelling conditional variance of each route through ARMA-GARCH process, the time-varying standard deviation was extracted in order to compare the degree of variation among the trading lines. Since in dynamic portfolio formation both the risk and the returns are considered, Conditional Coefficient of Variation (CCV) was defined as a volatility measure. CCV was calculated as conditional standard deviation over absolute actual returns. The CV allows determining how much volatility, or risk, you are assuming in comparison to the amount of return you can expect from the investment. The lower this ratio, the better the risk-return tradeoff. Finally, after computing the mean CCV of all the CCFI routes and performing statistical tests we could confidently support which route is more volatile. A descriptive statistics based on the CCV will be initially presented in **Table 5.14**.

Table 5.14: *Conditional Coefficient of Variation for the CCFI and its trading lines*

	CCFI	North America EC	Europe	Hong Kong	Japan	Korea
Mean	4,945	6,823	5,302	4,769	8,747	5,283
Median	2,887	2,906	1,760	1,461	3,810	1,584
Maximum	56,017	142,877	141,034	260,494	320,961	225,236
Minimum	1,482	1,217	0,092	0,224	2,227	0,207
Std. Dev.	6,396	14,318	12,220	15,848	23,268	17,239
	Medit/nean	**South America**	**S/E Asia**	**West Africa**	**North America WC**	
Mean	5,8875	6,5508	4,5791	8,1010	6,9501	
Median	1,7155	1,8803	1,4090	2,7058	3,0040	
Maximum	246,3693	790,1173	248,3865	409,6435	188,6604	
Minimum	0,1039	0,0659	0,2238	0,0937	1,1757	
Std. Dev.	18,1637	18,1637	15,0224	23,4155	15,7326	

5.1.4.1 Parametric tests' procedure

On a descriptive statistics basis, the route of Japan has the higher mean conditional coefficient of variation (CCV), implying that has also the higher volatility on its freight rate returns. However, this mean value is only a point estimation based on a sample of time-series data. Therefore, any sample differences among mean values of CCV's don't necessary imply statistical significant differences of populations' mean values meaning that there is indeed higher volatility for one route compared to another route. Formal statistical inference should be conducted in order to appropriately test whether any sample differences are actually statistically significant.

Taking the mean value of CCVs as appropriate trend measure overtime in order to compare freight returns volatility among routes, and noting $\mu_1, \mu_2, \ldots, \mu_{10}$ the populations mean CCVs, the relevant hypotheses should be stated as follows:

H_0: $\mu_1 = \mu_2 = \ldots = \mu_{10}$

H_1: one mean value is different compared to others

As CCVs data have come from time-series data, they are supposed to have some correlations with each other. Therefore, we have to treat these measured as dependent and, thus, 2-way ANOVA without interaction is the appropriate parametric test. Results are presented in **Table 5.15**

Table 5.15: *2-Way ANOVA without interaction for mean CCVs comparisons among routes for the CCFI.*

Variance Source	*SS*	*d.f*	*MS*	*F*	*P-value*
Rows	256.095,78	665	385,11	0,962	0,73
Columns (CCV)	11.780,49	9	1.308,94	3,27*	0,0005
Error	2.394.733,57	5985	400,12		
Total	2.662.609,84	6659			

** Significant at 1% level*

F-statistic for rows is not so high in 5% level (p-value > 0.05), implying that there is no difference among the row mean CCV over time. However, F-statistic for columns is high enough even in 1% level (p-value < 0.01) implying that mean CCVs are not all equal for all routes. Therefore, it can be inferred that freight returns volatility is not the same for all routes, measured by the mean CCV.

This inference, however, doesn't necessary imply that each route has statistically different volatility compared to volatilities of all other routes. This inference implies that at least one route has statistically different volatility compared to others. In order to infer which route has statistically different volatility compared to other, post-hoc[17] tests should be conducted comparing two routes mean CCV every time. Given that data have already considered as dependent measures, pairwise t-test is the appropriate parametric test in this case.

As there are 10 routes to compare each other, there are 45 pairs to be tested. This number is really large. An idea in order to reduce the number of tests is to rank, first, the 10 routes according to sample mean CCV and, then, to test whether there are any statistical differences between the first and second, then, between the second and the third and so on. The ranking based on mean CCV is presented in **Table 5.16**.

17 Post-hoc analysis (from Latin *post-hoc* "after this") refers to testing the data for patterns that were not specified a priori. Post-hoc analysis is a required procedure without which multivariate hypothesis testing would greatly suffer, rendering the chances of discovering false positives unacceptably high.

Therefore, first mean CCV of Japan route is statistically compared to mean CCV of W/E Africa route. Then mean CCV of W/E Africa route is statistically compared to mean CCV North America WC route. It should be noted that if no statistical difference is found in one pair, then similar tests are conducted between pairs, until a significant difference is found. For example, if no statistical difference between Japan and W/E Africa mean CCV is found, then a pairwise t-test will be conducted between mean CCV of Japan and North America WC and so on.

Table 5.16: *Mean CCV per Route for CCFI*

Route	Mean CCV
Japan	8,75
West/East Africa	8,10
North America West Coast	6,95
North America East Coast	6,82
South America	6,55
Meditterranean	5,88
Europe	5,30
Korea	5,28
Hong-Kong	4,77
South/East Asia	4,55

Results of all pairwise t-test are presented in **Table 5.17**. It should be noted that the test is conducted as one-tailed test, in a sense that we care to test whether freight rate returns volatility is statistically higher for one route compared to another one.

Table 5.17: *Pairwise t-tests for mean CCV between routes (t-statistics) for CCFI*

	West/East Africa	North America West Coast	North America East Coast	South America	Med/nean	Europe	Korea	Hong-Kong	South/East Asia
Japan	0,508	1,69**							
West/East Africa	-	1,05	1,19	0,96	1,91**				
North America West Coast		-	0,14	0,26	1,11	2,13**			
North America East Coast			-	0,18	1,05	2,09**			
South America				-	0,44	0,88	0,85	1,37*	
Meditterranean					-	0,71	0,62	1,31*	
Europe						-	0,02	0,72	0,97
Korea							-	0,55	0,88
Hong-Kong								-	0,25

***, * indicate significance at 5% and 10% level respectively*

Japan route freight rate volatility returns is statistically higher in 5%, compared to North America WC volatility and, consequently, to other routes which are found lower volatility. West/East Africa route volatility is statistically higher in 5%, compared to Mediterranean route. North America WC and North America EC routes volatilities are higher in 5% compared to Europe route volatility and, consequently, to all other routes which are found lower volatility. South America and Mediterranean routes volatility are statistically higher in 5% level compared to Hong-Kong route volatility and, consequently, to South-East Asia route volatility. Finally, Europe, Korea and Hong-Kong were not found to have statistically higher volatility compared to South-East Asia route volatility.

These pairwise t-tests reveal, actually, some clusters of routes that their freight rate returns perform higher or lower volatility. The more the black the color of the route the higher the volatility is found. These results are presented in **Table 5.18**.

Table 5.18: *Volatility Ranking per Route for CCFI*

Route	Mean CCV
Japan	8,75
West/East Africa	8,10
North America West Coast	6,95
North America East Coast	6,82
South America	6,55
Meditterranean	5,88
Europe	5,30
Korea	5,28
Hong-Kong	4,77
South/East Asia	4,55

Another test that was conducted in order to examine freight rate returns volatility in each route is to compare volatility of each route, based on mean CCV, with that of CCFI, in a sense that this index represents an aggregate level of all routes indices. Again due to time-series mode of data, pairwise t-tests were considered as the most appropriate technique. Results are presented in **Table 5.19**.

Table 5.19: *Volatility Comparison between Routes and CCFI*

Route	Mean CCV	t-statistic
Japan	8,75	4,07***
West/East Africa	8,10	3,46***
North America West Coast	6,95	3,08***
North America East Coast	6,82	3,09***
South America	6,55	1,18
Meditterranean	5,88	1,27
Europe	5,30	0,66
Korea	5,28	0,46
CCFI Composite Index	4,95	-
Hong-Kong	4,77	-0,26
South/East Asia	4,55	-0,61

**** Significant at 1% level*

The high volatile routes like Japan, West Africa, North America WC and North America EC were found to have statistically higher mean volatility in 1% level (p-value < 0.01) compared to CCFI mean volatility. Routes with lower volatility like South America, Mediterranean, Europe and Korea were found to have no statistically higher mean volatility compared to CCFI mean volatility. Finally, Hong-Kong and South East Asia routes were found to have statistically lower mean volatility compared to CCFI mean volatility.

5.1.4.2 Non-parametric tests' procedure

Parametric procedure followed in the previous section, requires some specific assumptions in order to run on a reliable way. One vital assumption is normality of sample data or at least a large sample. Indeed, sample is quite large (N = 667) meaning that F-statistics and t-statistics follow, at least approximately the relevant distribution and, thus, parametric test conducting produced reliable results.

However, another important issue is whether it is meaningful to consider the average value of CCVs as a representative measure of tendency. Actually, if CCV distribution is far from a symmetrical one, median level is considered as a better measure of tendency and, thus, in order to compare volatilities of all routes, we should compare their median level of CCV. Indeed, there are some reasonable differences between mean and median values for each route. Therefore, it seems that parametric test may not produce reliable results and some relevant non-parametric test should be conducted instead. Moreover, non-parametric test will be useful in order to confirm and enhance parametric test results.

First, Friedman test is conducted as the analogous F-test of 2-Way ANOVA for dependent measures. Chi-square statistic is high enough, even in 1% level (p-value < 0.01) implying that the null hypothesis of equal medians is rejected. Therefore, it is meaningful to proceed to test median differences on a post-hoc context comparing two samples each time. The ranking of each route is presented with criterion the median value of CCV. Results are presented in **Table 5.20**.

Table 5.20: *Routes Volatility Ranking According to Median CCV for CCFI*

Route	Median CCV
Japan	3,81
North America West Coast	3,00
North America East Coast	2,91
West/East Africa	2,71
South America	1,88
Europe	1,76
Meditterranean	1,72
Korea	1,57
Hong-Kong	1,46
South/East Asia	1,41

Ranking using median CCV as criterion is almost the same as the ranking using mean CCV. Only West East Africa route have slightly different ranking. This ranking is a first note that results will be almost the same. However, non-parametric pairwise test should be conducted. The appropriate non-parametric criterion is the Wilcoxon Z-test. Results are presented in the **Table 5.21.**

Table 5.21: *Non-Parametric Pairwise tests for median CCV between routes (Z-statistics)*

	North America West Coast	North America East Coast	West/East Africa	South America	Europe	Med/nean	Korea	Hong-Kong	South/ East Asia
Japan	5,35***	6,1***	4,69***	10,38***	10,39***	10,47***	12,48***	13,7***	14,12***
North America West Coast	-	0,29	1,62	7,01***	7,14***	6,85***	8,72***	11,52***	10,54***
North America East Coast		-	1,08	6,41***	7,61***	7,06***	8,83***	10,71***	10,62***
West/East Africa			-	5,28***	5,74***	5,48***	7,01***	8,46***	8,69***
South America				-	0,75	0,74	2,31**	3,81***	3,44***
Europe					-	0,66	2,12**	3,39***	3,06***
Meditterranean						-	2,2**	3,6***	3,87***
Korea							-	1,12	2,01**
Hong-Kong								-	0,17

******* *Significant in 1% level, ** Significant in 5% level*

In most pairs, the null hypothesis for equal medians is rejected ether in 1% or in 5% level (p-value < 0.01 or p-value < 0.05). However, according to the non-parametric test, the clusters are a bit different than in the parametric procedure. **Table 5.22** summarizes the clusters associated.

Table 5.22: *Non-Parametric Ranking according to Wilcoxon Signed Ranked test for CCFI*

Route	Median CCV
Japan	3,81
North America West Coast	3,00
North America East Coast	2,91
West/East Africa	2,71
South America	1,88
Europe	1,76
Medditerranean	1,72
Korea	1,57
Hong-Kong	1,46
South/ East Asia	1,41

Using the same Wilcoxon test procedure, it is also examined whether the median level of CCFI volatility is statistically different compared to median level of all routes volatility. Results are presented in **Table 5.23.**

Table 5.23: *Volatility Comparison between CCFI and Routes – Wilcoxon test*

Route	Median CCV	Z-Statistic
Japan	3,81	8,7***
North America West Coast	3,00	0,74
North America East Coast	2,91	0,55
CCFI Composite Index	2,88	-
West/East Africa	2,71	0,15
South America	1,88	6,88***
Europe	1,76	7,14***
Medditerranean	1,72	6,94***
Korea	1,57	8,77***
Hong-Kong	1,46	10,38***
South/ East Asia	1,41	10,79***

**** Significant in 1% level, Z statistic in absolute value*

The highly volatile route like Japan is found to have statistically higher median volatility in 1% level (p-value < 0.01) compared to CCFI median volatility. Routes with lower median volatility like North America WC, North America EC and W/E Africa are found to have no statistically higher median volatility compared to CCFI median volatility. Finally, routes with even lower median volatility, like South America, Europe Mediterranean, Korea, Hong Kong and South East Asia are found to have statistically lower median volatility compared to CCFI.

Summarizing, results of both parametric and non-parametric test reveal a ranking in freight rate returns volatility, based on mean or median CCV, where routes in big seas like the Pacific Ocean (Japan, North America WC, South America) or Atlantic Ocean (West Africa, North America EC, South America) seem to perform statistically higher volatility. On the contrary, volatility is statistically lower in routes with not so big seas like Mediterranean or Europe and it is even statistically smaller in regional seas like Korea, Hong-Kong and South East Asia.

5.2 Empirical Results for the Baltic Dry Index (BDI), Baltic Clean Tanker Index (BDTI), Baltic Dirty Tanker Index (BDTI) and China Containerized Freight Index (CCFI)

According to the second part of this thesis, the same procedure will be followed in order to compare the volatility among CCFI, BDI, BCTI and BDTI. The analysis of CCFI has already been done in the previous section. The results are only presented for comparison.

5.2.1 Procedure for model selection- the mean equation

Autocorrelation and partial autocorrelation functions of BDI, BCTI and BDTI are presented in **Appendix 6** which suggest possible ARMA models for modeling the mean equation. Based solely on the information criterion SIC, various ARMA (p,q) models were fitted to the daily returns of the indices. The results, according to the lowest value of SIC, are presented on **Table 5.24:**

Table 5.24 *ARMA selection according to SIC for the freight markets*

Baltic Dry Index (BDI)	ARMA(0,4)
Baltic Clean Tanker Index (BCTI)	ARMA(1,1)
Baltic Dirty Tanker Index (BDTI)	ARMA(1,1)
China Containerized Freight Index (CCFI)	ARMA(1,1)

5.2.2 Procedure for model selection- the variance equation

Appendix 7 presents the ACF and PACF of squared residuals of estimated ARMA models. Again, joint specification of the conditional mean and conditional variance take place as well as the estimation of E-GARCH (1,1) and T-GARCH (1,1) with Normal, Student-t and GED distributions. **Appendix 8** presents the results, as well as, **Table 5.26** to **Table 5.28** present the estimated outputs and the misspecification test associated.

5.2.3 Output analysis

Table 5.25: *Summary of the estimated models for the BDI, BCTI, BDTI and CCFI*

	Selected ARMA-GARCH Models	Distribution
Baltic Dry Index (BDI)	ARMA(1,1)-GARCH(1,1)	Student's T
Baltic Clean Tanker Index (BCTI)	ARMA(1,1)-ARCH(1)	Student's T
Baltic Dirty Tanker Index (BDTI)	ARMA(3,0)- EGARCH (1,1)	Student's T
China Containerized Freight Index (CCFI)	ARMA(1,2)-GARCH(1,1)	Student's T

- ***GARCH(1,1) model***

The first category consists of the BDI whose conditional variance can be modelled by GARCH (1,1). The coefficients $alpha_0$ (constant), $alpha_1$ (ARCH term) and $beta_1$ (GARCH term) are highly significant and the non-negativity condition is satisfied. The sum of the persistence coefficients ($Alpha_1$, $Beta_1$) is less than one which is required for stationarity in variance. Finally, the LjBox Q statistics of standardized residuals confirms that the mean equation of the model is adequate. Both the LjBoxQ of the squared standardized residuals and the ARCH-LM test confirm that the variance equation is adequate too.

- ***ARCH (1,1) model***

The BCTI can be modelled properly by an ARCH (1) model with student's t distribution. This indicates that only lagged squared innovations have an impact on the conditional variance.

- ***E-GARCH (1,1) model***

The BDTI can be modelled properly by an E-GARCH (1,1) model. All the coefficients and C(3) which captures the asymmetries in volatility, are significant.

Table 5.26: *Output for ARMA(1,1)-GARCH(1,1) model for the BDI*

Dependent Variable BDI ***GARCH(1,1) estimation with Student-t***				
Variable	**Estimated Coefficient**	**Standard Error**	**z-statistic**	**P-value**
C	0.004264	0.004031	1.057894	0.2901
AR(1)	0.319983	0.060621	5.278379	0.0000
MA(1)	0.368879	0.059034	6.248618	0.0000
Variance Equation				
Alpha0	0.000127	5.27E-05	2.410872	0.0159
Alpha1	0.132538	0.032108	4.127854	0.0000
Beta1	0.844675	0.035365	23.88465	0.0000
T-DIST. DOF	9.181822	3.006865	3.053619	0.0023
Se	0.065339			
RBS	0.333737			
DW	2.099072			
LL	966.9726			
SIC	-2.781003			
LjBQ(10)	4.0786	(0.666)		
LjBQS(10)	10.957	(0.204)		
SK(eh)	-0.096139			
KU (eh)	4.050358			
ARCH TEST F-STATISTIC	0.003424	(0.9534)		

Table 5.27: *Output for ARMA(1,1)-ARCH(1) model for the BCTI*

Dependent Variable BCTI ***ARCH(1) estimation with Student-t***				
Variable	**Estimated Coefficient**	**Standard Error**	**z-statistic**	**P-value**
C	-0.008920	0.002918	-3.056552	0.0022
AR(1)	0.471229	0.043414	10.85422	0.0000
MA(1)	0.305083	0.046680	6.355593	0.0000
Variance Equation				
Alpha0	0.001026	0.000129	7.969547	0.0000
Alpha1	0.493060	0.133060	3.705538	0.0002
T-DIST. DOF	3.886096	0.482801	8.049056	0.0000
Se	0.043507			
RBS	0.273983			
DW	2.355350			
LL	1305.192			
SIC	-3.786834			
LjBQ(10)	5.6763	(0.683)		
LjBQS(10)	1.6788	(0.989)		
SK(eh)	0.377776			
KU (eh)	18.63016			
ARCH TEST F-STATISTIC	0.074734	(0.7846)		

Table 5.28: *Output for ARMA(3,0)-E-GARCH(1,1) model for the BDTI*

Dependent Variable BDTI E-GARCH(1,1) estimation with Student-t				
Variable	**Estimated Coefficient**	**Standard Error**	**z-statistic**	**P-value**
C	0.003242	0.002773	1.168888	0.2424
AR(1)	0.536921	0.031617	16.98222	0.0000
AR(2)	-0.227294	0.035595	-6.385598	0.0000
AR(3)	0.086081	0.032610	2.639676	0.0083
Variance Equation				
C(1)	-0.138032	0.048616	-2.839229	0.0045
C(2)	0.113908	0.032828	3.469893	0.0005
C(3)	0.186527	0.034341	5.431679	0.0000
C(4)	0.990380	0.007217	137.2249	0.0000
T-DIST. DOF	4.176707	0.702265	5.947477	0.0000
Se	0.061949			
RBS	0.224523			
DW	1.995225			
LL	1019.951			
SIC	-2.926503			
LjBQ(10)	9.1698	(0.241)		
LjBQS(10)	11.536	(0.117)		
SK(eh)	0.440234			
KU (eh)	6.782580			
ARCH TEST F-STATISTIC	0.034390	(0.8529)		

5.2.4 Volatility Comparisons Through Conditional Coefficient of Variation

A descriptive statistics based on the CCV of CCFI, BDI, BCTI and BDTI is initially presented in **Table 5.29**.

Table 5.29: *Conditional Coefficient of Variation for the CCFI, BDI, BCTI and BDTI.*

	CCFI	**BDI**	**BDTI**	**BCTI**
Mean	4,945	8,062	6,363	5,277
Median	2,550	3,389	2,880	2,672
Maximum	56,017	295,247	239,518	137,671
Minimum	1,482	2,207	1,179	1,407
Std. Dev.	6,396	23,369	15,327	9,596

5.2.4.1 Parametric tests' procedure

On a descriptive statistics basis, the BDI index has the higher mean conditional coefficient of variation (CCV), implying that has also the higher volatility on its freight rate returns. However, this mean value is only a point estimation based on a sample of time-series data. Therefore, any sample differences among mean values of CCV's don't necessary imply statistical significant differences of populations' mean values meaning that there is indeed higher volatility for one index compared to another index. Formal statistical inference should be conducted in order to appropriately test whether any sample differences are actually statistically significant.

Taking the mean value of CCVs as appropriate trend measure overtime in order to compare freight returns volatility among indices, and noting $\mu_1, \mu_2, \mu_3, \mu_4$ the populations' mean CCVs, the relevant hypotheses should be stated as follows:

H_0: $\mu_1 = \mu_2 = \mu_3 = \mu_4$

H_1: one mean value is different compared to others

As CCVs data have come from time-series data, they are supposed to have some correlations with each other. Therefore, we have to treat these measured as dependent and, thus, 2-way ANOVA without interaction is the appropriate parametric test. Results are presented in **Table 5.30:**

Table 5.30: *2-Way ANOVA without interaction for mean CCVs comparisons among indices*

Variance Source	*SS*	*d.f*	*MS*	*F*	*p-value*
Rows (Items)	156.360,15	667	234,42	1,02	0,39
Columns (CCV)	4.198,57	3	1.399,52	6,07*	0,00
Error	460.934,70	2001	230,35		
Total	621.493,42	2671			

** Significant at 1% level*

F-statistic for rows is not so high in 10% level (p-value > 0.10), implying that there is no difference among the row means CCV over time. F-statistic for columns is high enough in 1% level (p-value < 0.01) implying that mean CCVs are not equal for all indices. Therefore, it can be inferred that freight returns volatility may be not the same for all indices, measured by the mean CCV.

This inference, however, doesn't necessary imply that each index has statistically different volatility compared to volatilities of all other indices. This inference implies that at least one index has statistically different volatility compared to others. In order to infer which index has statistically different volatility compared to other, post-hoc tests should be conducted comparing two indices mean CCV every time. Given that data have already considered as dependent measures, pairwise t-test is the appropriate parametric test in this case. Mean CCVs are presented in **Table 5.31.**

Results of all pairwise t-test are presented in the **Table 5.32**. It should be noted that the test is conducted as one-tailed test, in a sense that we care to test whether freight rate returns volatility is statistically higher for one index compared to another one.

Table 5.31: *Mean CCV per Index*

Index	Mean CCV
BDI	8,14
BDTI	6,35
BCTI	5,25
CCFI	4,95

Table 5.32: *Pairwise t-tests for mean CCV between indices (t-statistics)*

	BDTI	BCTI	CCFI
BDI	1,62	3,01***	3,39***
BDTI	-	1,56*	2,21**
BCTI		-	0,65

****,**,* indicate significance at 1%, 5% and 10% respectively*

BDI freight rate returns volatility is statistically higher in 1%, compared to BCTI and CCFI volatility. BDTI returns volatility is higher in 10% compared to BCTI and consequently to CCFI index returns volatility.

These pairwise t-tests reveal, actually, some clusters of indices that their freight rate returns perform higher or lower volatility. The more the black the color of the index the higher the volatility is found. These results are presented in **Table 5.33**.

Table 5.33: *Volatility Ranking per Index*

	Mean CCV
BDI	8,14
BDTI	6,35
BCTI	5,25
CCFI	4,95

5.2.4.2 Non-parametric tests' procedure

Parametric procedure followed in the previous section, requires some specific assumptions in order to run on a reliable way. One vital assumption is normality of sample data or at least a large sample. Indeed, sample is quite large (N = 668) meaning that F-statistics and t-statistics follow, at least approximately the relevant distribution and, thus, parametric test conducting produced reliable results.

However, another important issue is whether it is meaningful to consider the average value of CCVs as a representative measure of tendency. Actually, if CCV distribution is far from a symmetrical one, median level is considered as a better measure of tendency and, thus, in order to compare volatilities of all indices we should compare their median level of CCV between all indices. Indeed, there are some reasonable differences between mean and median values for each index. Therefore, it seems that parametric test may not produce reliable results and some relevant non-parametric test should be conducted instead.

First, Friedman test is conducted as the analogous F-test of 2-Way ANOVA for dependent measures. Chi-square statistic is high enough, even in 1% level (p-value < 0.01) implying that the null hypothesis of equal medians is rejected. Therefore, it is meaningful to proceed to test median differences on a post-hoc context comparing two samples each time. The ranking of each index is presented with criterion the median value of CCV. Results are presented in **Table 5.34:**

Table 5.34: *Indices Volatility Ranking According to Median CCV*

Index	Median CCV
BDI	3,39
BDTI	2,88
BCTI	2,66
CCFI	2,55

Based on median CCVs, ranking remains the same. However, non-parametric pairwise test should be conducted. The appropriate non-parametric criterion is the Wilcoxon Z-test. Results are presented in the **Table 5.35**:

Table 5.35: *Non-Parametric Pairwise tests for median CCV between indices (Z-statistics)*

	BDTI	BCTI	CCFI
BDI	6,82***	10,45***	12,35***
BDTI	-	5,23***	7,18***
BCTI		-	3,32***

** **Significant in 1% level*

In all pairs, the null hypothesis for equal medians is rejected in 1% level (p-value < 0.01). Therefore, based on these results, it can be inferred that there are statistically significant differences among median CCVs for all indices each other. This means that, according to non-parametric test, each index has statistically higher or lower volatility compared to other indices volatility.

Summarizing, results of both parametric and non-parametric tests reveal a ranking in freight rate returns volatility, based on mean or median CCV, where BDI index seem to perform statistically higher volatility. Volatility is statistically lower in all other indices. More particularly, according to pairwise t-tests, BDTI index seems to perform the second higher volatility, compared to BCTI and CCFI index, BCTI seems to perform the third higher volatility and, finally, CCFI index seems to perform the lower volatility compared to all other indices.

VI. Conclusion

In the first part of this thesis, volatility comparison took place concerning freight rate log-returns of certain CCFI routes. Volatility was measured by the conditional coefficient of variation (CCV) which was calculated by dividing conditional standard deviation over absolute actual returns. According to unit root tests, log-returns for all routes are stationary and, thus, ARMA model could be fitted in order to model properly the conditional mean. Moreover, in order to model the conditional variance in a time-varying framework, ARCH-GARCH models (and others related) were also fitted. Applying SIC criterion, the best model for both conditional mean and conditional variance was selected.

After conditional variances estimations were held, conditional coefficients of variation were indirectly estimated. Using those estimations as proxy of volatility their mean level was compared among routes. More particularly, estimated averages were compared in a context of parametric tests and estimated median were compared in a context of non-parametric tests. Comparisons took place among routes volatilities each other and between each route volatility and the CCFI volatility. Moreover, comparisons took place among several indices (CCFI, BDI, BDTI, and BCTI).

Results of both parametric and non-parametric tests revealed some statistical significant differences between mean levels of time-varying volatility among routes. More particularly, volatility was found statistically higher in route of Japan, compared to all other routes. Then, routes of West Africa and North America WC performed higher volatility compared to other routes. Routes like North America EC, South America, and Mediterranean as well as Europe performed slightly lower volatility being in the middle level. Then, routes like Korea and Hong-Kong performed much lower volatility and, finally, South-East Asia route performed the statistically lower volatility.

It should be mentioned that non-parametric tests produced more statistical significant differences. This is because non-parametric tests tend to produce less power of test (i.e. higher probability of type II error), meaning that they tend to reject on a more frequent basis. Therefore, we have to carefully interpret all statistically significant differences. However, both parametric and non-parametric tests produced similar volatilities ranking among routes.

Results show that routes involving big seas, like Pacific and Atlantic oceans, were found to perform the higher volatility in freight rate returns compared to volatility of routes involving not so big seas like Europe and Mediterranean. Moreover, routes involving even smaller seas like Korea, Hong-Kong and South-East Asia were found to perform even lower freight rate returns volatility. It seems that when a route involves a big sea, then there are a lot of dangers arise. The most probable danger is the weather conditions that exist in such big seas and make the trip more uncertain.

Another issue is trip distance. It seems that the longer the distance, the higher the uncertainty is. This is why routes far from China, involving two big Oceans and seas in Europe perform higher freight rate returns volatility and routes close to China, like Korea, Hong-Kong and South-East Asia perform the lower freight rate volatility.

Concerning freight rate returns volatility comparison among indices, both parametric and non-parametric tests revealed that BDI performs the higher volatility. Then, BDTI performs the second higher volatility, while BCTI performs the third higher volatility and, finally, CCFI performs the lower volatility compared to other indices.

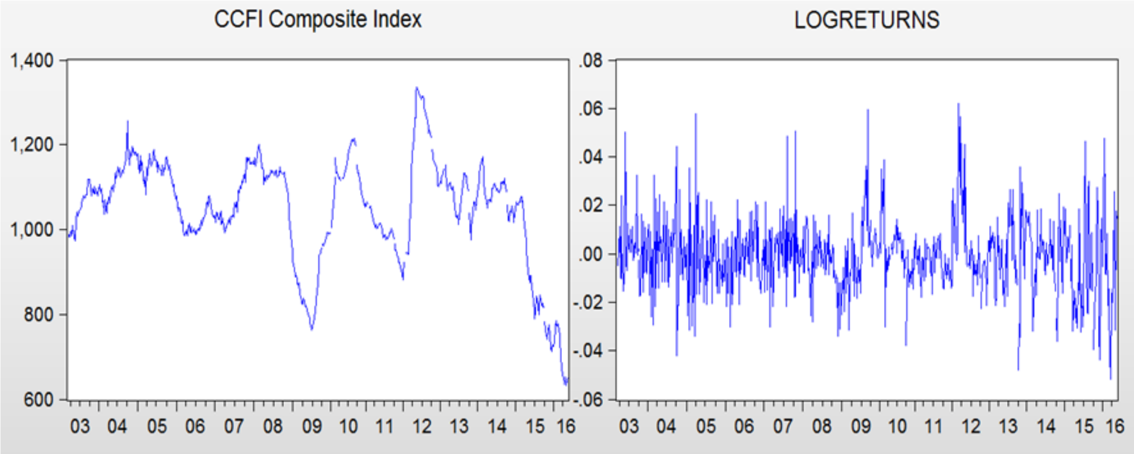
The results seem to be in accordance to Kavussanos (1996) and Kavussanos (2003) results, concerning BDTI and BCTI volatilities comparison, in a sense that BDTI was found to be more volatile compared to BCTI. Actually, BDTI involves larger ships compared to BCTI and it has been found that freights in larger ships are more volatile compared to freights in smaller ones. Therefore, the vessels size explains BDTI higher volatility over BCTI volatility. However, results are not in accordance with Angelidis and Skiadopoulos (2008) results, where BDTI volatility has been found to be higher compared to BDI volatility. In our research we found that BDI is more volatile than BDTI. Maybe this difference is due to the fact that their research was conducted before the financial crisis.

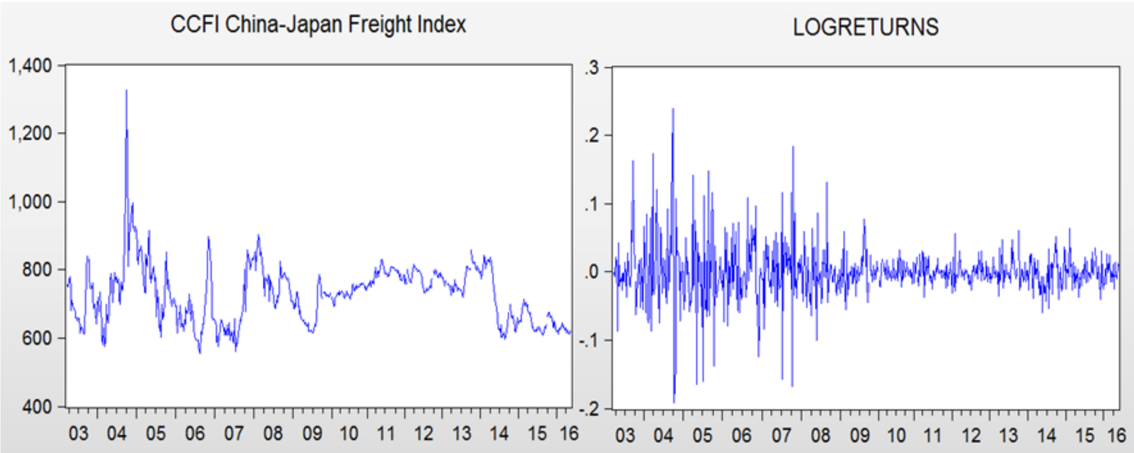
Finally, there is no previous research (to the author's knowledge) of why CCFI was ranked as the least volatile index. However, a possible explanation is that containership market is not as attractive as dry bulk or tanker market and thus, it does not have a significant trading volume that leads to lower freight rate volatility.

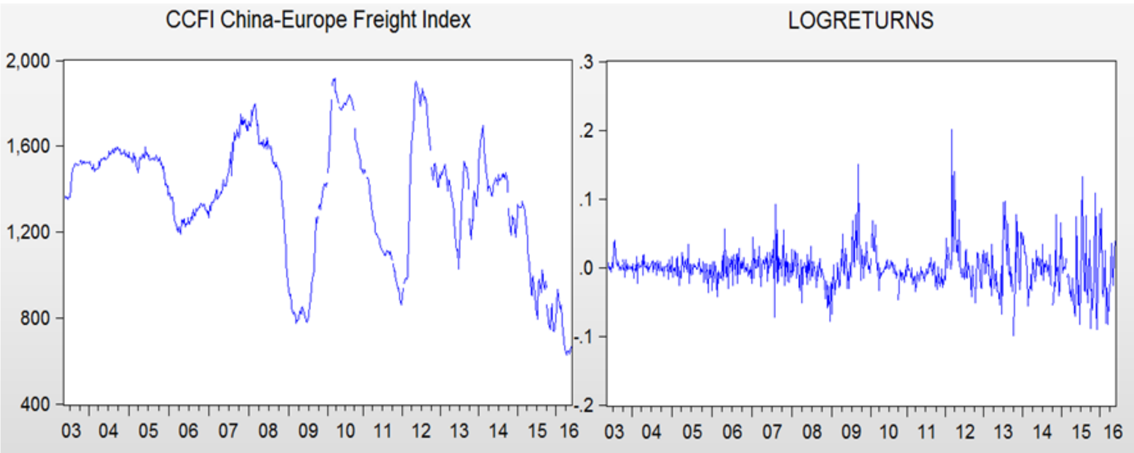
Therefore, it was found that volatility is higher in cases of larger vessels, of cargos implied higher uncertainty and involving longer routes passing from big seas. This is actually normal, in a sense that the more the factors of uncertainty involved in a trip, the higher the freight rate returns volatility. This finding is fully consistent with financial theory of risk, where the higher the risk, the higher the returns premium associated.

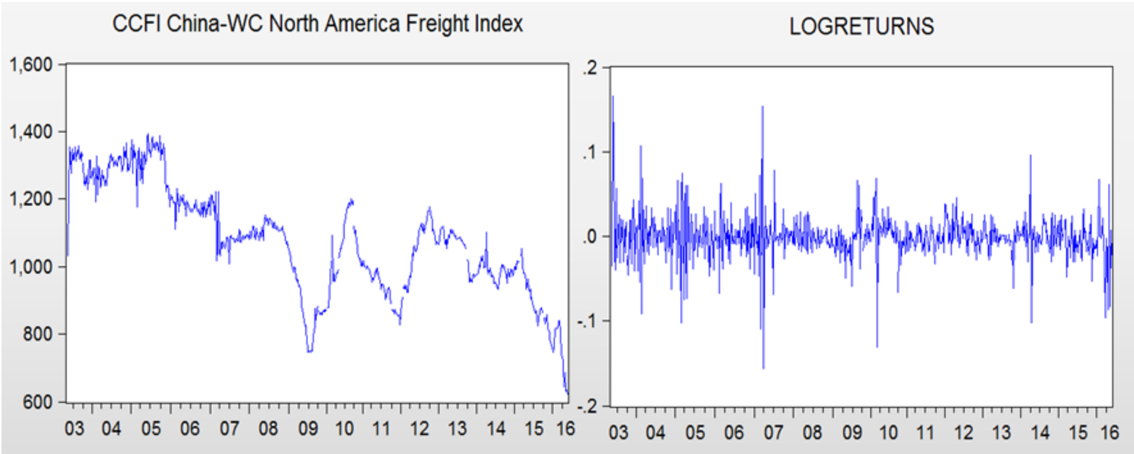
VII. Appendices

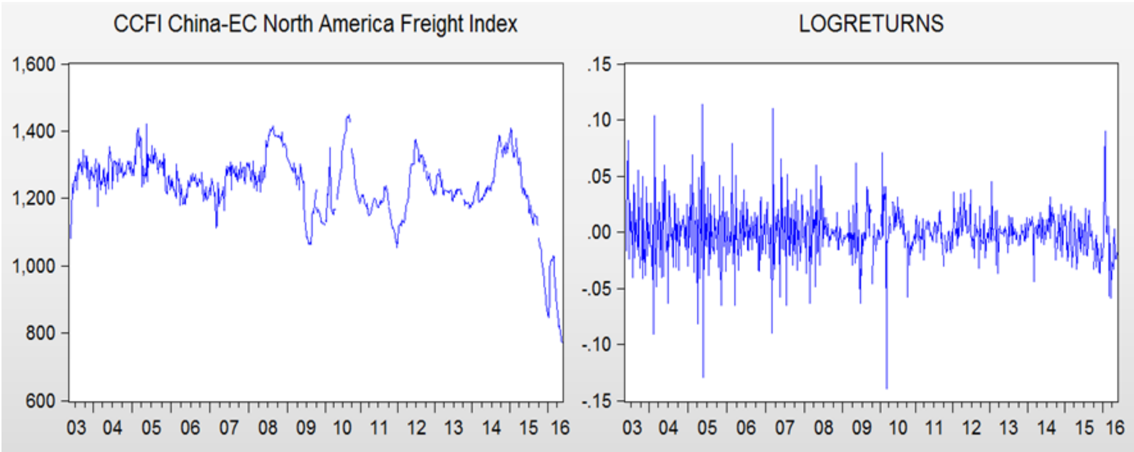
Appendix 1: *Graphical representation of Price and log-returns for the CCFI and its routes (2003-2016).*

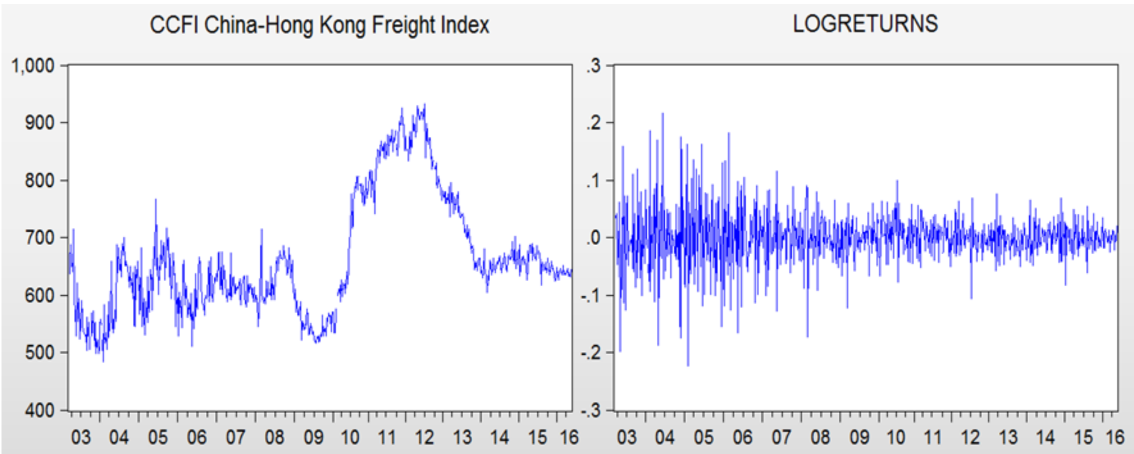


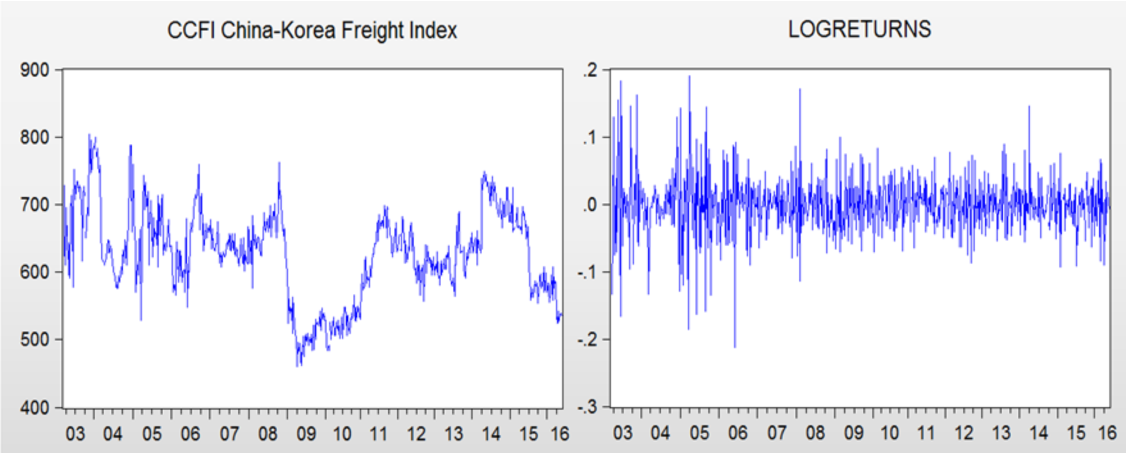


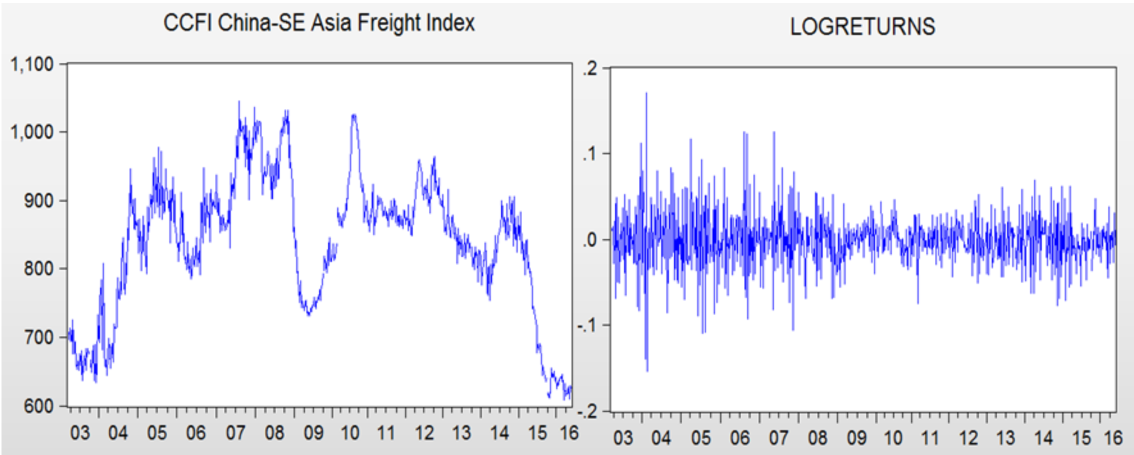


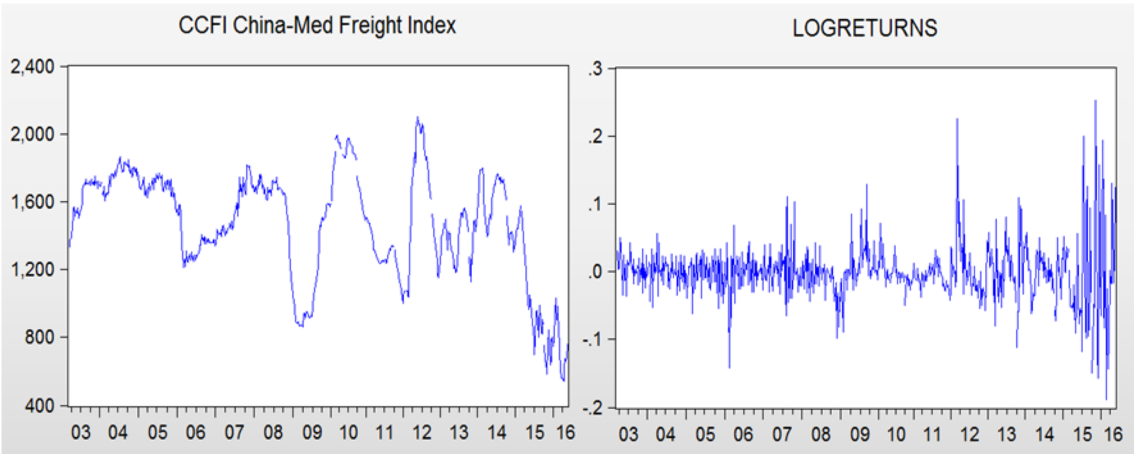

CCFI China-WC North America Freight Index
1,600
1,400
1,200
1,000
800
600
03 04 05 06 07 08 09 10 11 12 13 14 15 16
LOGRETURNS
.2
.1
.0
-.1
-.2
03 04 05 06 07 08 09 10 11 12 13 14 15 16

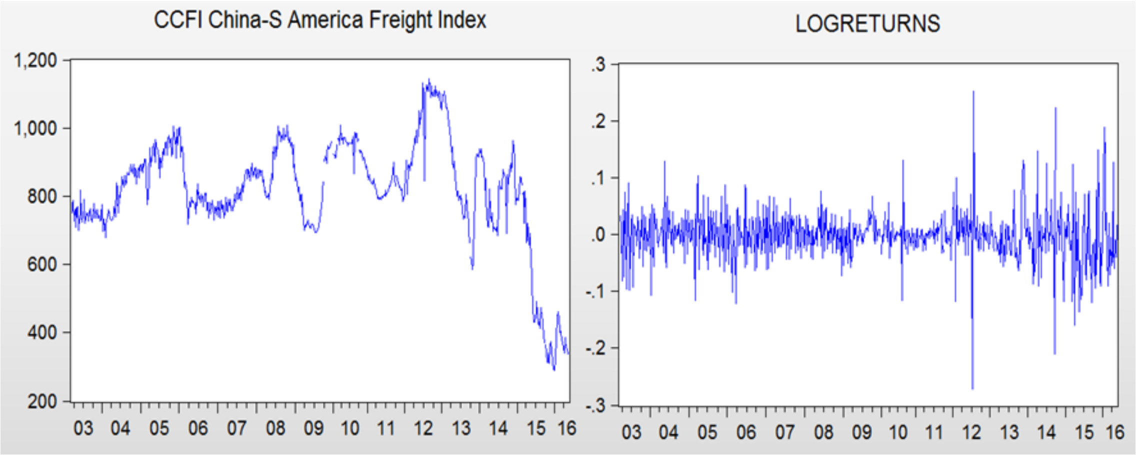

CCFI China-EC North America Freight Index
1,600
1,400
1,200
1,000
800
600
03 04 05 06 07 08 09 10 11 12 13 14 15 16
LOGRETURNS
.15
.10
.05
.00
-.05
-.10
-.15
03 04 05 06 07 08 09 10 11 12 13 14 15 16

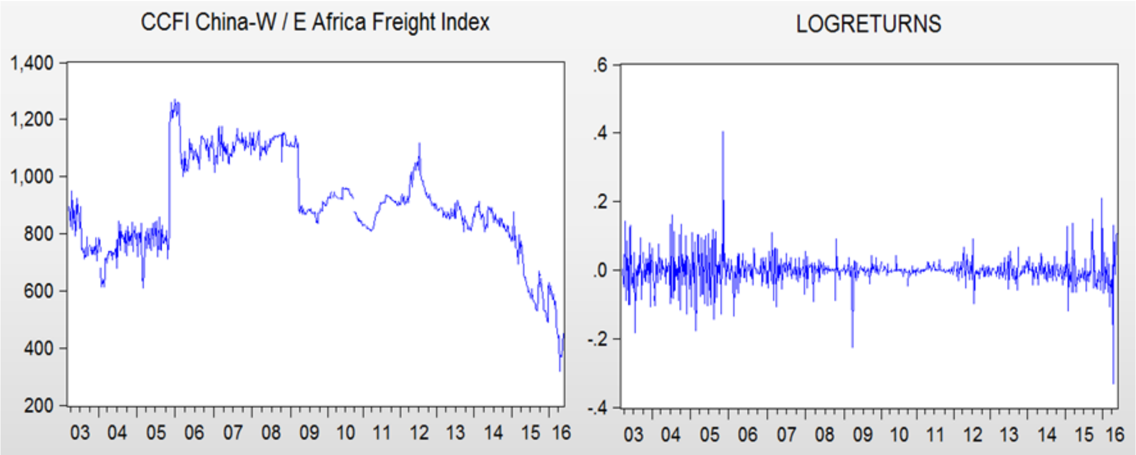

CCFI China-Hong Kong Freight Index
1,000
900
800
700
600
500
400
03 04 05 06 07 08 09 10 11 12 13 14 15 16
LOGRETURNS
.3
.2
.1
.0
-.1
-.2
-.3
03 04 05 06 07 08 09 10 11 12 13 14 15 16


CCFI China-Korea Freight Index
900
800
700
600
500
400
03 04 05 06 07 08 09 10 11 12 13 14 15 16
LOGRETURNS
.2
.1
.0
-.1
-.2
-.3
03 04 05 06 07 08 09 10 11 12 13 14 15 16

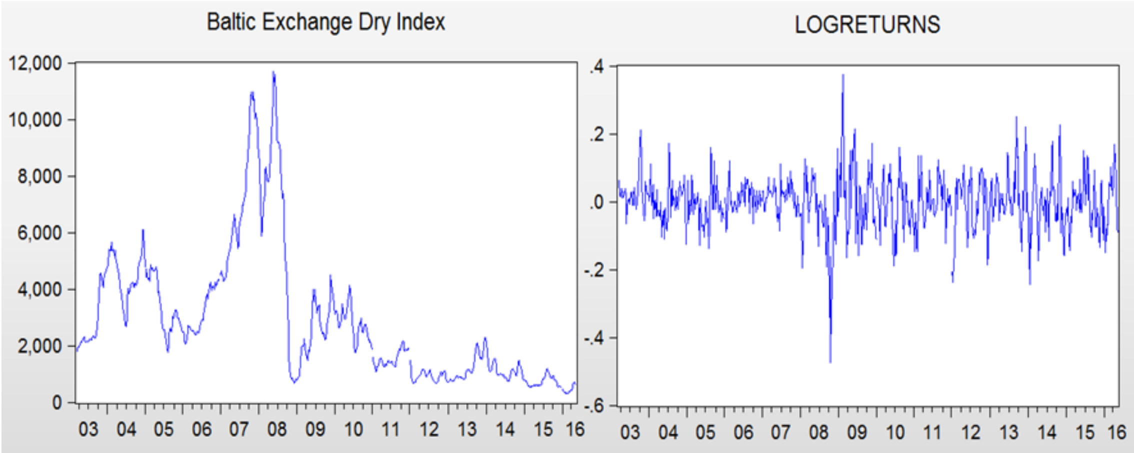

CCFI China-SE Asia Freight Index
1,100
1,000
900
800
700
600
03 04 05 06 07 08 09 10 11 12 13 14 15 16
LOGRETURNS
.2
.1
.0
-.1
-.2
03 04 05 06 07 08 09 10 11 12 13 14 15 16

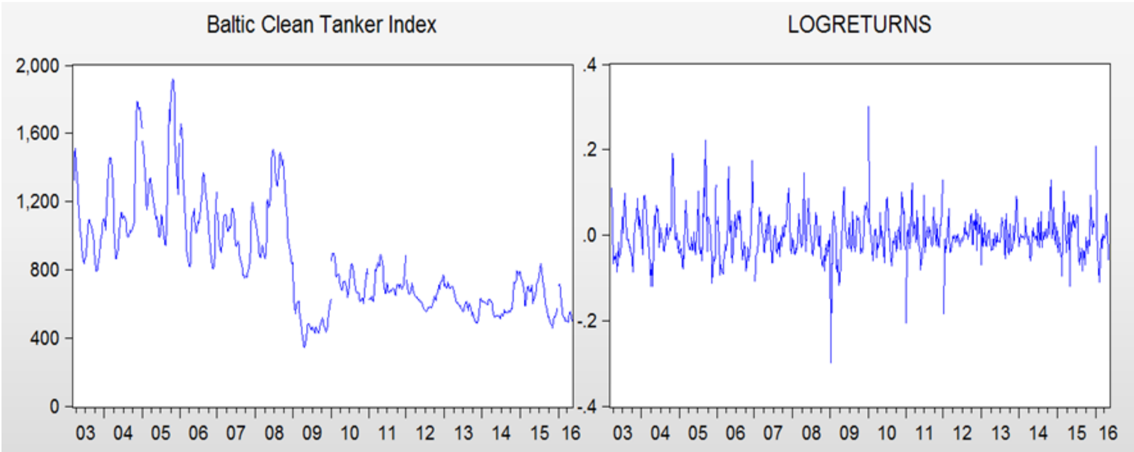

CCFI China-Med Freight Index
2,400
2,000
1,600
1,200
800
400
03 04 05 06 07 08 09 10 11 12 13 14 15 16
LOGRETURNS
.3
.2
.1
.0
-.1
-.2
03 04 05 06 07 08 09 10 11 12 13 14 15 16

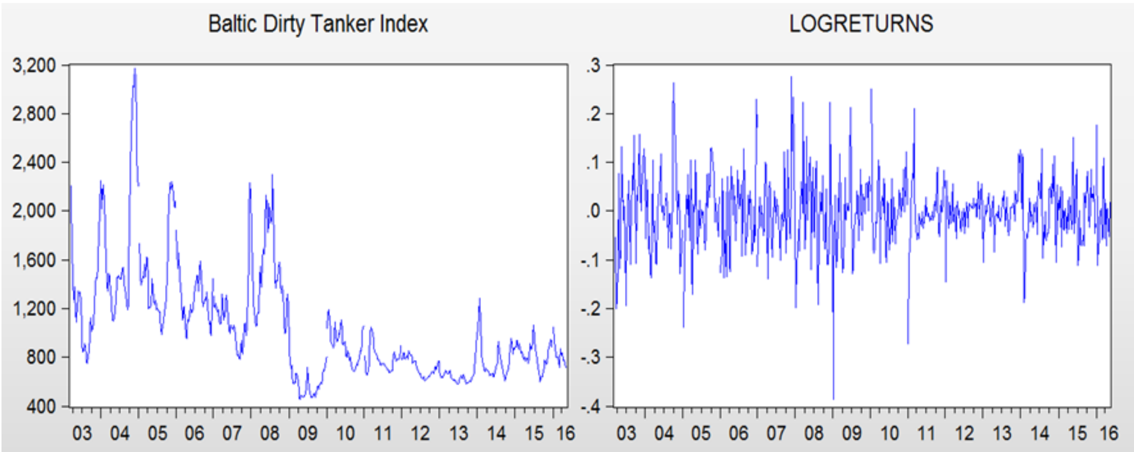

CCFI China-S America Freight Index
LOGRETURNS


CCFI China-W / E Africa Freight Index
LOGRETURNS

Appendix 2: *Graphical representation of Price and log-returns of the BDI, BCTI and BDTI (2003-2016).*







Appendix 3: *ACF and PACF of log returns of CCFI and its routes*

Date: 05/25/16 Time: 13:15
Sample: 5/16/2003 5/13/2016
Included observations: 661

	AC	PAC	Q-Stat	Prob
1	0.189	0.189	23.839	0.000
2	0.225	0.196	57.446	0.000
3	0.143	0.077	71.042	0.000
4	0.140	0.070	84.086	0.000
5	0.071	-0.001	87.438	0.000
6	0.051	-0.009	89.149	0.000
7	0.068	0.034	92.250	0.000
8	0.054	0.021	94.185	0.000
9	0.024	-0.012	94.567	0.000
10	-0.027	-0.057	95.049	0.000

1. ACF and PACF of CCFI

Date: 05/25/16 Time: 14:05
Sample: 5/16/2003 5/13/2016
Included observations: 661

	AC	PAC	Q-Stat	Prob
1	-0.062	-0.062	2.5187	0.113
2	0.022	0.018	2.8331	0.243
3	-0.101	-0.099	9.6674	0.022
4	0.006	-0.007	9.6891	0.046
5	-0.050	-0.047	11.332	0.045
6	0.032	0.016	11.997	0.062
7	-0.043	-0.040	13.218	0.067
8	0.041	0.027	14.343	0.073
9	-0.055	-0.047	16.396	0.059
10	-0.036	-0.053	17.270	0.069

2. ACF and PACF of China-Japan

Date: 05/25/16 Time: 14:02
Sample: 5/16/2003 5/13/2016
Included observations: 661

	AC	PAC	Q-Stat	Prob
1	0.328	0.328	71.493	0.000
2	0.194	0.096	96.462	0.000
3	0.162	0.082	113.95	0.000
4	0.148	0.069	128.58	0.000
5	0.102	0.016	135.49	0.000
6	0.083	0.019	140.05	0.000
7	0.090	0.038	145.52	0.000
8	0.084	0.027	150.28	0.000
9	-0.004	-0.070	150.29	0.000
10	-0.105	-0.131	157.72	0.000

3. ACF and PACF of China-Europe

Date: 05/25/16 Time: 14:00
Sample: 5/16/2003 5/13/2016
Included observations: 661

	AC	PAC	Q-Stat	Prob
1	-0.181	-0.181	21.742	0.000
2	0.002	-0.031	21.745	0.000
3	0.081	0.078	26.071	0.000
4	0.003	0.034	26.079	0.000
5	0.053	0.064	27.968	0.000
6	-0.048	-0.035	29.515	0.000
7	-0.004	-0.023	29.525	0.000
8	-0.031	-0.049	30.186	0.000
9	-0.059	-0.073	32.551	0.000
10	0.013	-0.010	32.670	0.000

4. ACF and PACF of China-N. America EC

Date: 05/25/16 Time: 14:10
Sample: 5/16/2003 5/13/2016
Included observations: 661

	AC	PAC	Q-Stat	Prob
1	-0.205	-0.205	28.032	0.000
2	-0.056	-0.102	30.105	0.000
3	0.058	0.026	32.340	0.000
4	0.086	0.104	37.284	0.000
5	-0.005	0.047	37.301	0.000
6	0.030	0.053	37.922	0.000
7	-0.025	-0.017	38.352	0.000
8	-0.011	-0.030	38.429	0.000
9	0.000	-0.022	38.429	0.000
10	0.033	0.022	39.161	0.000

5. ACF and PACF of China-N. America WC

Date: 05/25/16 Time: 14:03
Sample: 5/16/2003 5/13/2016
Included observations: 661

	AC	PAC	Q-Stat	Prob
1	-0.471	-0.471	147.35	0.000
2	0.026	-0.251	147.81	0.000
3	0.023	-0.109	148.17	0.000
4	-0.012	-0.056	148.26	0.000
5	-0.036	-0.082	149.14	0.000
6	0.038	-0.029	150.11	0.000
7	-0.016	-0.020	150.27	0.000
8	-0.005	-0.021	150.29	0.000
9	0.074	0.083	153.96	0.000
10	-0.030	0.071	154.57	0.000

6. ACF and PACF of China-Hong Kong

Date: 05/25/16 Time: 14:06
Sample: 5/16/2003 5/13/2016
Included observations: 661

	AC	PAC	Q-Stat	Prob
1	-0.334	-0.334	74.035	0.000
2	-0.029	-0.159	74.610	0.000
3	-0.003	-0.078	74.617	0.000
4	-0.006	-0.045	74.637	0.000
5	0.062	0.048	77.216	0.000
6	-0.042	-0.003	78.377	0.000
7	0.025	0.024	78.799	0.000
8	-0.032	-0.019	79.472	0.000
9	-0.036	-0.060	80.340	0.000
10	0.008	-0.042	80.384	0.000

7. ACF and PACF of China-Korea

Date: 05/25/16 Time: 14:09
Sample: 5/16/2003 5/13/2016
Included observations: 661

	AC	PAC	Q-Stat	Prob
1	-0.507	-0.507	170.72	0.000
2	0.161	-0.129	187.95	0.000
3	-0.070	-0.060	191.24	0.000
4	0.140	0.131	204.36	0.000
5	-0.130	0.006	215.60	0.000
6	0.082	0.015	220.13	0.000
7	-0.020	0.029	220.39	0.000
8	0.047	0.057	221.86	0.000
9	-0.048	0.015	223.44	0.000
10	-0.024	-0.080	223.81	0.000

8. ACF and PACF of China- SE Asia

Date: 05/25/16 Time: 14:07
Sample: 5/16/2003 5/13/2016
Included observations: 661

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.223	0.223	32.886	0.000
		2	-0.006	-0.058	32.909	0.000
		3	0.016	0.032	33.088	0.000
		4	0.177	0.175	54.015	0.000
		5	0.084	0.005	58.731	0.000
		6	-0.097	-0.117	65.041	0.000
		7	-0.018	0.036	65.263	0.000
		8	0.035	-0.002	66.099	0.000
		9	0.068	0.044	69.198	0.000
		10	-0.122	-0.123	79.179	0.000

9. ACF and PACF of China-Mediterranean

Date: 05/25/16 Time: 14:08
Sample: 5/16/2003 5/13/2016
Included observations: 661

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.112	-0.112	8.2655	0.004
		2	-0.020	-0.033	8.5395	0.014
		3	0.023	0.017	8.8838	0.031
		4	-0.041	-0.037	9.9827	0.041
		5	-0.023	-0.031	10.329	0.066
		6	0.010	0.002	10.396	0.109
		7	0.011	0.012	10.470	0.163
		8	0.007	0.009	10.501	0.232
		9	0.007	0.008	10.538	0.309
		10	-0.016	-0.014	10.701	0.381

10. ACF and PACF of China-S. America

Date: 05/25/16 Time: 14:09
Sample: 5/16/2003 5/13/2016
Included observations: 661

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.507	-0.507	170.72	0.000
		2	0.161	-0.129	187.95	0.000
		3	-0.070	-0.060	191.24	0.000
		4	0.140	0.131	204.36	0.000
		5	-0.130	0.006	215.60	0.000
		6	0.082	0.015	220.13	0.000
		7	-0.020	0.029	220.39	0.000
		8	0.047	0.057	221.86	0.000
		9	-0.048	0.015	223.44	0.000
		10	-0.024	-0.080	223.81	0.000

11. ACF and PACF of China- W.E Africa

Appendix 4: *ACF and PACF of squared residuals of estimated ARMA (p,q) models for the CCFI and its routes*

Date: 06/07/16 Time: 20:00
Sample: 4/11/2003 5/13/2016
Included observations: 666
Q-statistic probabilities adjusted for 2 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.179	0.179	21.494	
		2	0.102	0.072	28.396	
		3	0.115	0.089	37.292	0.000
		4	0.023	-0.018	37.654	0.000
		5	0.055	0.040	39.688	0.000
		6	0.042	0.017	40.870	0.000
		7	0.051	0.037	42.613	0.000
		8	0.062	0.037	45.217	0.000
		9	0.062	0.037	47.809	0.000
		10	-0.026	-0.060	48.267	0.000

1. ARMA (1,1) -CCFI

Date: 07/11/16 Time: 23:00
Sample: 3/28/2003 5/13/2016
Included observations: 668
Q-statistic probabilities adjusted for 2 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.497	0.497	165.42	
		2	0.340	0.124	243.13	
		3	0.189	-0.028	267.05	0.000
		4	0.105	-0.014	274.43	0.000
		5	0.113	0.076	283.11	0.000
		6	0.048	-0.043	284.67	0.000
		7	0.097	0.083	291.04	0.000
		8	0.028	-0.060	291.56	0.000
		9	0.079	0.080	295.83	0.000
		10	0.029	-0.048	296.40	0.000

2. ARMA (1,1)-Japan

Date: 06/07/16 Time: 20:09
Sample: 4/11/2003 5/13/2016
Included observations: 666
Q-statistic probabilities adjusted for 2 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.043	0.043	1.2626	
		2	0.076	0.074	5.1006	
		3	0.232	0.227	41.156	0.000
		4	0.102	0.087	48.154	0.000
		5	0.055	0.021	50.159	0.000
		6	0.070	0.005	53.442	0.000
		7	0.090	0.045	58.867	0.000
		8	0.099	0.074	65.503	0.000
		9	0.061	0.033	68.032	0.000
		10	0.050	0.004	69.705	0.000

3. ARMA (1,1)-Europe

Date: 07/11/16 Time: 23:03
Sample: 4/11/2003 5/13/2016
Included observations: 666
Q-statistic probabilities adjusted for 2 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.413	0.413	114.00	
		2	0.167	-0.004	132.68	
		3	0.129	0.074	143.89	0.000
		4	0.122	0.053	153.96	0.000
		5	0.036	-0.049	154.84	0.000
		6	0.024	0.018	155.23	0.000
		7	0.021	-0.001	155.53	0.000
		8	0.019	0.006	155.78	0.000
		9	-0.010	-0.022	155.85	0.000
		10	0.001	0.012	155.85	0.000

4. ARMA (2,0) – North America W.C.

Date: 07/11/16 Time: 23:06
Sample: 4/11/2003 5/13/2016
Included observations: 666
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.225	0.225	33.958	
		2	0.092	0.044	39.639	0.000
		3	0.007	-0.024	39.669	0.000
		4	0.017	0.018	39.872	0.000
		5	0.054	0.051	41.811	0.000
		6	0.044	0.021	43.125	0.000
		7	0.109	0.093	51.105	0.000
		8	0.103	0.062	58.256	0.000
		9	0.057	0.011	60.475	0.000
		10	0.009	-0.016	60.524	0.000

5. ARMA (1,0)-North America E.C

Date: 07/11/16 Time: 23:09
Sample: 4/11/2003 5/13/2016
Included observations: 666
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.178	0.178	21.315	
		2	0.158	0.130	38.047	0.000
		3	0.090	0.045	43.530	0.000
		4	0.152	0.117	59.133	0.000
		5	0.125	0.073	69.644	0.000
		6	0.088	0.025	74.872	0.000
		7	0.198	0.157	101.40	0.000
		8	0.084	0.001	106.22	0.000
		9	0.112	0.040	114.68	0.000
		10	0.162	0.114	132.43	0.000

6. ARMA (0,1)-Hong Kong

Date: 06/07/16 Time: 20:32
Sample: 4/11/2003 5/13/2016
Included observations: 666
Q-statistic probabilities adjusted for 5 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.241	0.241	38.723	
		2	0.162	0.110	56.236	
		3	0.133	0.077	68.071	
		4	0.041	-0.022	69.193	
		5	0.073	0.048	72.799	
		6	0.004	-0.034	72.809	0.000
		7	0.085	0.084	77.655	0.000
		8	0.060	0.020	80.059	0.000
		9	0.093	0.069	85.913	0.000
		10	0.094	0.037	91.878	0.000

7. ARMA (2,3)-Korea

Date: 07/11/16 Time: 23:11
Sample: 4/11/2003 5/13/2016
Included observations: 666
Q-statistic probabilities adjusted for 2 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.198	0.198	26.304	
		2	0.183	0.150	48.833	
		3	0.154	0.099	64.661	0.000
		4	0.197	0.140	90.846	0.000
		5	0.101	0.015	97.718	0.000
		6	0.182	0.116	119.96	0.000
		7	0.098	0.010	126.48	0.000
		8	0.115	0.034	135.41	0.000
		9	0.139	0.074	148.47	0.000
		10	0.080	-0.017	152.80	0.000

8. ARMA (0,2)-SE Asia

Date: 07/11/16 Time: 23:13
Sample: 4/11/2003 5/13/2016
Included observations: 666
Q-statistic probabilities adjusted for 6 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.147	0.147	14.367	
		2	0.179	0.161	35.810	
		3	0.237	0.201	73.558	
		4	0.149	0.081	88.499	
		5	0.240	0.168	127.26	
		6	0.117	0.012	136.53	
		7	0.121	0.022	146.47	0.000
		8	0.111	-0.001	154.83	0.000
		9	0.223	0.159	188.63	0.000
		10	0.076	-0.035	192.51	0.000

9. ARMA (2,4)-Mediterranean

Date: 07/11/16 Time: 23:23
Sample: 4/11/2003 5/13/2016
Included observations: 666
Q-statistic probabilities adjusted for 3 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.112	0.112	8.4430	
		2	0.047	0.035	9.9376	
		3	0.048	0.040	11.510	
		4	0.041	0.030	12.623	0.000
		5	0.060	0.050	15.037	0.001
		6	0.017	0.001	15.231	0.002
		7	0.031	0.022	15.860	0.003
		8	0.010	-0.002	15.923	0.007
		9	0.009	0.002	15.976	0.014
		10	0.018	0.012	16.200	0.023

10. ARMA (1,2)-W.E. Africa

Date: 06/07/16 Time: 20:48
Sample: 4/11/2003 5/13/2016
Included observations: 666
Q-statistic probabilities adjusted for 1 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.279	0.279	52.236	
		2	0.160	0.089	69.375	0.000
		3	0.023	-0.046	69.731	0.000
		4	0.035	0.028	70.538	0.000
		5	0.026	0.017	71.003	0.000
		6	0.038	0.023	71.992	0.000
		7	0.028	0.010	72.522	0.000
		8	0.034	0.019	73.314	0.000
		9	0.047	0.033	74.830	0.000
		10	0.010	-0.018	74.900	0.000

11. ARMA (1,0)- S. America

Appendix 5: *SIC outputs for model selection with Normal, Student and GED error distribution. Numbers highlighted in blue indicate the model selected according to SIC.*

Composite Index(CCFI)-ARMA(1,2)	NORMAL DISTRIBUTION			STUDENT-T			GED		
	GARCH(1,1)	T-GARCH (1,1)	E-GARCH(1,1)	GARCH(1,1)	T-GARCH (1,1)	E-GARCH(1,1)	GARCH(1,1)	TGARCH (1,1)	EGARCH(1,1)
Schwarz Information Criterion	-5,6160	-5,6124	-5,6057	**-5,6684**	-5,6608	-5,6582	-5,6607	-5,6527	-5,6487

Japan-ARMA(1,1)	NORMAL DISTRIBUTION			STUDENT-T			GED		
	GARCH(2,1)	T-GARCH (1,1)	E-GARCH(1,1)	GARCH(1,2)	T-GARCH (1,1)	E-GARCH(1,1)	GARCH(1,2)	T-GARCH (1,1)	EGARCH(1,1)
Schwarz Information Criterion	-4,116106	-4,116386	-4,111837	-4,216970	-4,204683	-4,198472	**-4,222036**	-4,190467	-4,202513

Europe-ARMA(1,1)	NORMAL DISTRIBUTION			STUDENT-T			GED		
	GARCH(1,1)	T-GARCH (1,1)	E-GARCH(1,1)	GARCH(1,1)	T-GARCH (1,1)	E-GARCH(1,1)	GARCH(1,1)	T-GARCH (1,1)	EGARCH(1,1)
Schwarz Information Criterion	-4,553848	-4,644470	-4,651272	-4,866693	-4,874143	**-4,879133**	-4,854720	-4,847453	-4,853267

N.Am WC-ARMA(1,0)	NORMAL DISTRIBUTION			STUDENT-T			GED		
	GARCH(1,1)	T-GARCH (1,1)	E-GARCH(1,1)	GARCH(1,1)	T-GARCH (1,1)	E-GARCH(1,1)	GARCH(1,1)	T-GARCH (1,1)	EGARCH(1,1)
Schwarz Information Criterion	-4,735773	-4,727829	-4,716591	**-4,852502**	-4,842900	-4,846554	-4,845242	-4,835412	-4,835097

N.Am EC-ARMA(2,1)	NORMAL DISTRIBUTION			STUDENT-T			GED		
	GARCH(1,1)	T-GARCH (1,1)	E-GARCH(1,1)	GARCH(1,1)	T-GARCH (1,1)	E-GARCH(1,1)	GARCH(1,1)	T-GARCH (1,1)	EGARCH(1,1)
Schwarz Information Criterion	-4,760140	-4,737117	-4,746129	**-4,875122**	-4,866115	-4,871814	-4,867877	-4,858907	-4,863756

Appendix 5: *SIC outputs for model selection with Normal, Student and GED error distribution. Numbers highlighted in blue indicate the model selected according to SIC. (continued)*

Hong Kong-ARMA(0,1)	NORMAL DISTRIBUTION			STUDENT-T			GED		
	GARCH(1,1)	T-GARCH (1,1)	E-GARCH(1,1)	GARCH(1,1)	T-GARCH (1,1)	E-GARCH(1,1)	GARCH(1,1)	T-GARCH (1,1)	EGARCH(1,1)
Schwarz Information Criterion	-3,7256500	-3,7149280	-3,7184380	-3,7495530	-3,7407640	-3,7428370	-3,7476620	-3,7383060	-3,7383060

Korea-ARMA(0,1)	NORMAL DISTRIBUTION			STUDENT-T			GED		
	ARMA(2,3)-GARCH (1,1)	TGARCH (1,1)	EGARCH(1,1)	GARCH(1,1)	TGARCH (1,1)	EGARCH(1,1)	GARCH(1,1)	TGARCH (1,1)	EGARCH (1,1)
Schwarz Information Criterion	-3,5967880	-3,6081990	-3,6026330	-3,6721420	-3,6623130	-3,6542810	-3,6564970	-3,6466620	-3,6395740

SE Asia-ARMA(0,2)	NORMAL DISTRIBUTION			STUDENT-T			GED		
	GARCH(1,1)	T-GARCH (1,1)	E-GARCH(1,1)	GARCH(1,1)	T-GARCH (1,1)	EGARCH(1,1)	GARCH(1,1)	T-GARCH (1,1)	EGARCH(1,1)
Schwarz Information Criterion	-4,2460710	-4,2424850	-4,2457930	-4,2458660	-4,2426810	-4,2459240	-4,2428500	-4,2396040	-4,2426170

Mediterranean-ARMA(1,1)	NORMAL DISTRIBUTION			STUDENT-T			GED		
	GARCH(1,1)	T-GARCH (1,1)	EGARCH(1,1)	GARCH(1,1)	T-GARCH (1,1)	EGARCH(1,1)	GARCH(1,1)	T-GARCH (1,1)	EGARCH(1,1)
Schwarz Information Criterion	-3,96272	-3,98098	-3,99202	-4,15682	-4,16063	-4,16109	-4,13877	-4,14678	-4,14788

S. America-ARMA(1,0)	NORMAL DISTRIBUTION			STUDENT-T			GED		
	GARCH(1,1)	T-GARCH (1,1)	EGARCH(1,1)	GARCH(1,1)	T-GARCH (1,1)	EGARCH(1,1)	GARCH(1,1)	T-GARCH (1,1)	EGARCH(1,1)
Schwarz Information Criterion	-3,561379	-3,552345	-3,552450	-3,727708	-3,722672	-3,733410	-3,702656	-3,694358	-3,702136

W.E Africa ARMA(1,0)	NORMAL DISTRIBUTION			STUDENT-T			GED		
	GARCH(1,1)	T-GARCH (1,1)	EGARCH(1,1)	GARCH(1,1)	T-GARCH (1,1)	EGARCH(1,1)	GARCH(1,1)	T-GARCH (1,1)	EGARCH (1,1)
Schwarz Information Criterion	-3,71164	-3,70003	-3,73387	-4,11620	-4,12464	-4,13118	-4,11149	-4,10384	-4,11642

Appendix 6: *ACF and PACF of log returns for BDI, BCTI and BDTI.*

Date: 06/02/16 Time: 14:49
Sample: 3/14/2003 6/10/2016
Included observations: 682

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.583	0.583	232.45	0.000
		2	0.289	-0.076	289.86	0.000
		3	0.178	0.062	311.65	0.000
		4	0.091	-0.037	317.38	0.000
		5	-0.075	-0.175	321.23	0.000
		6	-0.079	0.073	325.59	0.000
		7	-0.058	-0.022	327.92	0.000
		8	-0.033	0.032	328.67	0.000
		9	-0.031	-0.012	329.35	0.000
		10	-0.005	-0.000	329.37	0.000

1. ACF and PACF of BDI

Date: 07/11/16 Time: 23:27
Sample: 3/14/2003 5/13/2016
Included observations: 680

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.544	0.544	201.89	0.000
		2	0.234	-0.087	239.45	0.000
		3	0.086	-0.008	244.49	0.000
		4	-0.030	-0.082	245.13	0.000
		5	-0.117	-0.081	254.54	0.000
		6	-0.124	-0.014	265.21	0.000
		7	-0.114	-0.033	274.13	0.000
		8	-0.110	-0.041	282.42	0.000
		9	-0.102	-0.040	289.67	0.000
		10	-0.097	-0.045	296.15	0.000

2. ACF and PACF of BCTI

Date: 07/11/16 Time: 23:30
Sample: 3/14/2003 5/13/2016
Included observations: 680

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.448	0.448	137.10	0.000
		2	0.039	-0.203	138.13	0.000
		3	-0.029	0.053	138.71	0.000
		4	0.026	0.036	139.18	0.000
		5	-0.015	-0.070	139.34	0.000
		6	-0.090	-0.062	144.96	0.000
		7	-0.067	0.012	148.09	0.000
		8	-0.017	-0.006	148.29	0.000
		9	-0.042	-0.058	149.52	0.000
		10	-0.105	-0.071	157.20	0.000

3. ACF and PACF of BDTI

Appendix 7: *ACF and PACF of squared residuals of estimated ARMA (p,q) models for the for BDI, BCTI and BDTI.*

Date: 07/11/16 Time: 23:37
Sample: 3/21/2003 5/13/2016
Included observations: 680
Q-statistic probabilities adjusted for 4 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.094	0.094	6.0401	
		2	0.293	0.287	64.706	
		3	0.047	0.001	66.235	
		4	0.087	0.000	71.463	
		5	0.072	0.058	75.063	0.000
		6	0.079	0.050	79.328	0.000
		7	0.046	0.002	80.785	0.000
		8	0.083	0.048	85.558	0.000
		9	0.069	0.048	88.880	0.000
		10	0.069	0.022	92.196	0.000

1. ARMA (0,4)- BDI

Date: 07/11/16 Time: 23:41
Sample: 3/28/2003 5/13/2016
Included observations: 679
Q-statistic probabilities adjusted for 2 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.167	0.167	18.933	
		2	-0.011	-0.040	19.017	
		3	0.003	0.012	19.022	0.000
		4	-0.012	-0.016	19.127	0.000
		5	-0.019	-0.014	19.365	0.000
		6	-0.009	-0.004	19.423	0.001
		7	0.004	0.006	19.437	0.002
		8	0.013	0.011	19.548	0.003
		9	-0.011	-0.016	19.634	0.006
		10	-0.028	-0.024	20.167	0.010

2. ARMA(1,1)- BCTI

Date: 07/11/16 Time: 23:45
Sample: 3/28/2003 5/13/2016
Included observations: 679
Q-statistic probabilities adjusted for 2 ARMA term(s)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.028	0.028	0.5533	
		2	0.079	0.078	4.7753	
		3	0.018	0.014	4.9929	0.025
		4	0.157	0.151	21.809	0.000
		5	-0.013	-0.023	21.918	0.000
		6	0.010	-0.012	21.984	0.000
		7	-0.017	-0.020	22.191	0.000
		8	0.059	0.038	24.565	0.000
		9	0.006	0.012	24.591	0.001
		10	0.027	0.021	25.083	0.002

3. ARMA (1,1)- BDTI

Appendix 8: *SIC outputs for model selection with Normal, Student and GED error distribution. Numbers highlighted in blue indicate the model selected according to SIC.*

BDI- ARMA(1,1)	NORMAL DISTRIBUTION			STUDENT-T			GED		
	ARMA(1,1)-GARCH(1,1)	T-GARCH (1,1)	E-GARCH(1,1)	GARCH (1,1)	T-GARCH (1,1)	E-GARCH(1,1)	ARMA(1,1)-GARCH(1,1)	TGARCH (1,1)	EGARCH (1,1)
Schwarz Information Criterion	-2,750088	-2,739884	-2,740702	**-2,781003**	-2,751075	-2,753021	-2,755324	-2,745740	-2,753021

BCTI- ARMA(1,1)	NORMAL DISTRIBUTION			STUDENT-T			GED		
	ARCH(1)	T-ARCH (1,1)	E-GARCH(1,1)	ARCH (1)	T-ARCH (1,1)	E-GARCH(1,1)	ARCH (1)	TARCH (1,1)	EGARCH (1,1)
Schwarz Information Criterion	-3,51465	-3,53942	-3,54303	**-3,78683**	-3,78028	-3,77957	-3,73674	-3,74248	-3,73358

BDTI- ARMA(1,1)	NORMAL DISTRIBUTION			STUDENT-T			GED		
	ARMA(1,2) GARCH(1,1)	T-GARCH (1,1)	E-GARCH(1,1)	GARCH (1,1)	MA(1)- TGARCH (1,1)	AR(3)- EGARCH(1,1)	AR(3) GARCH (1,1)	MA(1)- TGARCH (1,1)	AR(3)- EGARCH(1,1)
Schwarz Information Criterion	-2,75343	-2,73186	-2,81613	-2,88543	-2,90686	**-2,92650**	-2,88956	-2,90686	-2,90069

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Shanghai International Shipping Institute:

http://en.sisi-smu.org/