T.C.
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GRADUATE SCHOOL OF SOCIAL SCIENCES
DEPARTMENT OF MARITIME BUSINESS ADMINISTRATION
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MASTER'S THESIS

ANALYSIS OF LEVERAGE EFFECT IN CONTAINER FREIGHT INDICES BASED ON EGARCH MODEL

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THESIS APPROVAL PAGE

DECLARATION

I hereby declare that this master's thesis / project titled as "ANALYSIS OF LEVERAGE EFFECT IN CONTAINER FREIGHT INDICES BASED ON EGARCH MODEL" has been written by myself in accordance with the academic rules and ethical conduct. I also declare that all materials benefited in this thesis consist of the mentioned resources in the reference list. I verify all these with my honor.

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ÖZET

Yüksek Lisans Tezi

KONTEYNER NAVLUN ENDEKSLERİNDE EGARCH MODELİNE DAYALI KALDIRAÇ ETKİSİ ANALİZİ

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Tezin amacı tarifeli denizcilik piyasasında kaldıraç etkisinin özelliklerini incelemektir. Bu bağlamda temel tarifeli deniz taşımacılığı göstergeleri olan CCFI & SCFI'in 2010 ve 2018 yılları arasındaki getiri verileri Üssel Genelleştirilmiş Otoregresif Koşullu Değişen Varyans (EGARCH) Modeli kullanılarak incelenmiştir. Ampirik analiz sonuçları her iki endeksin de belirgin bir kaldıraç etkisine sahip olduklarını göstermektedir, bu da dış şokların tarifeli

denizcilik piyasasına olan etkisinin asimetrik olduğunu göstermektedir. Buna ek olarak her iki endeksin de negatif kaldıraç etkisine sahip olduğu saptanmış olup buradan negatif şokların ve haberlerin konteyner taşımacılığı sektöründe pozitif şoklar ve haberlerden daha fazla etkiye sahip olduğu sonucuna ulaşılmıştır.

Anahtar Kelimeler: Tarifeli Denizcilik, Kaldıraç Etkisi, EGARCH, Konteyner Navlun Endeksi, Zaman Serisi.

ABSTRACT

Master's Thesis

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Liner shipping market is considered as a seasonal, cyclical and highly volatile market. Due to the nonstationary and nonlinear nature of freight series and the complexity of influencing factors, it is difficult to analyze the fluctuations in the liner shipping market. China Containerized Freight Index (CCFI) and Shanghai Containerized Freight Index (SCFI) has been developed by the Shanghai Shipping Exchange to reflect the overall fluctuation level of international container shipping market. Nowadays, as an economic indicator CCFI & SCFI causes widespread concern by the shipping industry as well as the academic world about its characteristics and volatility. This thesis mainly focuses on the leverage effect, or in other words asymmetric volatility, in container shipping. The leverage effect helps us to understand the negative relationship between asset value and volatility.

The purpose is to examine the properties of leverage effect in main liner shipping indicators, namely CCFI and SCFI return data between 2010 and 2018 by employing an Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model. The results of empirical analysis show that both CCFI and SCFI have obvious leverage effects, meaning the impact of external shocks in liner shipping market is asymmetric. Both indices have negative leverage effect which means that negative shocks or in other words bad

news have more impact on the container shipping market than positive shocks or in other words good news.

Keywords: Liner Shipping, Leverage Effect, EGARCH, Container Freight Index, Time Series.

ANALYSIS OF LEVERAGE EFFECT IN CONTAINER FREIGHT INDICES BASED ON EGARCH MODEL

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CONTAINER FREIGHT INDICES

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CHAPTER THREE

ANALYSIS OF LEVERAGE EFFECT IN CONTAINER FREIGHT INDICES BASED ON EGARCH MODEL

LIST OF ABBREVIATIONS

AC	Autocorrelation
ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
AR	Autoregressive
ARCH	Autoregressive Conditional Heteroscedasticity
ARCH-LM	Autoregressive Conditional Heteroscedasticity Lagrange Multiplier
ARCH-M	Autoregressive Conditional Heteroscedasticity in Mean
ARMA	Autoregressive Moving Average
BAF	Bunker Adjustment Factor
BCI	Baltic Capesize Index
BCTI	Baltic Clean Tanker Index
BDI	Baltic Dry Index
BDTI	Baltic Dirty Tanker Index
BE	Baltic Exchange
BHI	Baltic Handysize Index
BLP	Bloomberg Limited Partnership
BPI	Baltic Panamax Index
CAF	Currency Adjustment Factor
CAP	Capital Asset Pricing
CCFI	China Containerized Freight Index
CCL	Consolidated Carriers Logistics
CIF	Cost Insurance Freight
COSCO	China Ocean Shipping Company
CRSL	Clarksons Research Services Limited
CSC	Carrier Security Charge
CY-CY	Container Yard to Container Yard
DMA	Drewry Maritime Advisors
EBA	Emergency Bunker Additional
EBAF	Emergency Bunker Adjustment Factor
EBS	Emergency Bunker Surcharge

EGARCH	Exponential Generalized Conditional Heteroscedasticity
EMS	Equipment Management Surcharge
ERS	Emergency Risk Surcharge
FAF	Fuel Adjustment Factor
FAK	Freight All Kinds
FBX	Freightos Baltic Global Container Index
FEU	Forty-foot Equivalent Unit
FFX	Freightos International Freight Index
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GAS	Gulf of Aden Surcharge
HQ	Hannan-Quinn Information Criterion
HR	Howe Robinson
ICAP	Inter-Capital
IGARCH	Integrated Generalized Autoregressive Conditional Heteroscedasticity
ILCC	Index Linked Container Contract
LL	Lloyd's List
LIBOR	London Interbank Offered Rate
LSS	Low Sulphur Surcharge
MA	Moving Average
ML	Maximum Likelihood
MOL	Mitsui OSK Lines
MSC	Mediterranean Shipping Company
NCFI	Ningbo Containerized Freight Index
NSE	Ningbo Shipping Exchange
NYK	Nippon Yusen Kaisha
OLS	Ordinary Least Squares
OOCL	Orient Overseas Container Line
PAC	Partial Correlation
PCC	Panama Canal Charge
PCS	Port Congestion Surcharge
PGARCH	Power Generalized Autoregressive Conditional Heteroscedasticity
PIL	Pacific International Lines

PP	Phillips-Perron
PRC	Peoples Republic of China
PSC	Port Security Charge
PSS	Peak Season Surcharge
PTF	Panama Canal Transit Fee
RAP	Risky Asset Pricing
RCCFI	Return of China Containerized Freight Index
RCL	Regional Container Lines
ROI	Return on Investment
RSCFI	Return of Shanghai Containerized Freight Index
SCF	Suez Canal Fee
SCFI	Shanghai Containerized Freight Index
SCS	Suez Canal Transit Surcharge
SIC	Schwarz Information Criterion
SSE	Shanghai Shipping Exchange
SSY	Simpson Spence & Young Shipbrokers
TEU	Twenty-foot Equivalent Unit
TGARCH	Threshold Generalized Autoregressive Conditional Heteroscedasticity
UNCTAD	United Nations Council of Trade and Development
USD	United Stated Dollars
USEC	United States East Coast
USWC	United Stated West Coast
Var	Variance
WCI	World Container Index
WRS	War Risk Surcharge
WS	World Scale
YAS	Yen Appreciation Surcharge

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INTRODUCTION

The CCFI and SCFI has been developed by the SSE to reflect the current situation and overall fluctuations of international container shipping market. Both indices are regarded highly as leading indicators for container shipping as well as international trade. SSE publishes both these composite indices and their sub-indices on weekly basis. Due to the recent developments in the impacting factors such as world economy, politics, and supply-demand relationships the container freight indices experienced violent fluctuations. This situation brings certain difficulties for stakeholders in container shipping market to make sound decisions. Therefore, understanding the characteristics of volatility has an utmost importance to avoid crucial risks both theoretically and practically. One of the most important factors for volatility to understand is the leverage effect phenomenon in this matter. The leverage effect or the asymmetric volatility is simply described as the negative relationship between asset value and volatility (Black, 1976).

To study the properties of volatility, Mandelbrot (1963) focused on the volatility clustering and found that high positive returns are followed by high negative returns, and low positive returns are followed by low negative returns. This set the basis for many studies conducted upon volatility and led to the proposition of Autoregressive Conditional Heteroscedasticity (ARCH) models. By pointing out that the residuals of the time series are not homoscedastic in most cases, Engle (1982) pointed out that in those cases the estimations can be made with the ARCH model. With more and more attention drown upon the subject, many improvements and extensions are made to ARCH model to remove many of the constraints and offer different aspects leading to improved estimation performance and asymmetric effect consideration. One such improvement made by Bollerslev (1986) to remove the constraint of unconditional variance having to be constant in ARCH models to create Generalized Conditional Heteroscedasticity (GARCH) model. After that Nelson (1991) proposed EGARCH model, which considers the signs of the lagged error terms of the conditional variance to account for the volatility asymmetry.

The first chapter of the study includes a detailed research on established and recently developed container freight indices and through examination was made on those indices.

In the second chapter a theoretical background to volatility and leverage effect were examined within the scope of models of changing volatility and models of asymmetric volatility. This chapter also sets the framework for the model and methodology to be used in the analyze process.

In the third chapter aim of the study is stated, the methodology is laid out, and selected data were prepared and financial time series estimations were conducted. The results of these volatility estimations were also given, discussed and conclusions were drawn at the end of the study.

CHAPTER ONE

CONTAINER FREIGHT INDICES

Shipping in general is known as a business with major unpredictability. Because of its close relations and interactions with the commodity markets, the global maritime transportation market possesses various business cycles. Stopford (2009) defines these cycles as long cycles, short business cycles, and seasonal cycles. To capture the fluctuations in the caused by these cycles, a number of highly regarded maritime and economical institutions developed various indices for this highly volatile market. The Table 1 summarizes the main suppliers of maritime transport indices and gives an outlook for their type distribution (Yifei et al., 2018).

Table 1: Main Suppliers and Types of Maritime Transport Indices

Ship	**Index**	**Supplier**									
		BE	**WS**	**CRSL**	**DMA**	**HR**	**ICAP**	**SSY**	**LL**	**BLP**	**SSE**
Tanker	**Earning**			√		√		√			
	Freight	√	√						√		√
	Finance				√		√		√	√	
Dry Bulk	**Earning**			√		√		√			
	Freight	√							√		√
	Finance				√		√		√	√	
Container Liner	**Earning**			√		√		√			
	Freight	√			√						√
	Finance				√		√		√	√	

BE - Baltic Exchange, WS – World Scale, CRSL – Clarksons Research Services Ltd, DMA – Drewry Maritime Advisors, HW – Howe Robinson, ICAP- Inter-Capital, SSY – Simpson Spence & Young Shipbrokers, LL – Lloyd's List, BLP – Bloomberg Limited Partnership, SSE – Shanghai Shipping Exchange.

Source: Yifei et al. 2018

The Baltic Exchange (BE) based in London, issues the most known and extensively used shipping freight index called the Baltic Dry Index (BDI) every working day. It is the composite index derived from the same institutions Baltic Capesize Index (BCI), Baltic Supramax Index (BSI), Baltic Panamax Index (BPI) and Baltic Handysize Index (BHI). That being said as of March 2018, the BE dropped BHI from the calculation of BDI and re-weighted the index to reflect 40% capsize, 30% panamax, and 30% supramax time charter averages. The BDI is globally considered as a major economic indicator, because of its interpretation of changes in the amount of raw materials traded in the global economy. The BE also publishes the Baltic Dirty Tanker Index (BDTI), and the Baltic Clean Tanker Index (BCTI), which the former being an index about the crude oil transport market, and the latter being an index about petroleum products transport market (Baltic Exchange, 2018).

Besides the BE, Clarksons Research Services (CRSL) one of the maritime industries leading statistics and research provider located in London and Shanghai also issues a number of indices related to charter market, such as ClarkSea Index and the Containership Time Charter Rate Index.

1.1.MAJOR CONTAINER FREIGHT INDICES

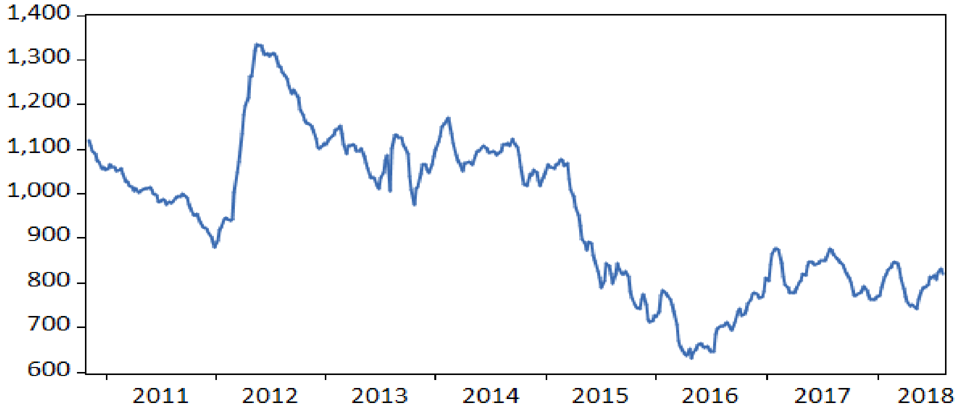
The container shipping market, being the youngest and fastest developing maritime transport market showed great increase of production in terms of indices and statistics. Due to the data sourcing issues, although there is no container freight index symbolized as BDI did in the dry bulk market, the SSE publishes the earliest and most used indices for the container shipping market, which will be discussed in detail in the later section. SSE being a government-bound organization funded by the Peoples Republic China (PRC), aims to provides consultancy, facilities and information to logistics and maritime industry. SSE harbors the principles of “Fairness, Openness and Impartiality” therefore, becomes an independent authority in maritime industry. SSE is bound to create and publish the freight indices guided strictly with "The Articles of China Containerized Freight Index Compiling Panel" and "The Rules of CCFI Compilation" (Shanghai Shipping Exchange, 2018).

1.1.1. China Containerized Freight Index (CCFI)

The main motivation behind the development of CCFI was to estimate and meet the demand of China's fast developing container transport market in the 1990s. To achieve this, Shanghai Shipping Exchange (SSE) managed to formulate the CCFI with the sponsorship of the China's Ministry of Transport in 13 April 1998. During the following years of its development, CCFI has gained recognition by its function as reflecting market movements and therefore started to be considered worldwide as the index that mirrors the economic and social effects to liner shipping industry. Due to its methodology and approach, CCFI is considered as one of the world's most potent freight index, only second to BDI. It has also been cited many times as authoritative statistics of the industry in the shipping annals published by United Nations Council of Trade and Development (UNCTAD) (Shanghai Shipping Exchange, 2018).

CCFI reflects the situation in container transport market and mirrors the China-bound freights to the world, which provides meticulously gathered information to various shipping and trading industry as well as the government agencies capable of regulating and controlling policies, thus attracting great attention of academia, consulting and financing companies and of course the media.

Figure 1: China Containerized Freight Index (CCFI)



Source: Processed by Author, Data from Bloomberg, 2018

1.1.1.1.Routes and Ports of Origin of CCFI

With their major principles being typicality, regional layout, and relativity kept in mind, SSE choose 12 trade routes as to be used as the samples. Which are; South Korea, Southeast Asia, Japan, Europe, East and West Africa, South Africa, United States West Coast (USWC), Mediterranean, United States East Coast (USEC), South America, Australia & New Zealand, Persian Gulf and Red Sea services. Each of the selected routes consist of departure ports in China including ten hub ports of the region. Them being; Dalian, Tianjin, Shanghai, Ningbo, Qingdao, Xiamen, Shenzhen, Nanjing, Guangzhou and Fuzhou. These 12 sub-indices are the main components of CCFI. SSE issues both the composite CCFI and the individual sub-indices for 12 trade routes on each Friday (Shanghai Shipping Exchange, 2018).

1.1.1.2.Panelists and Freight Information of CCFI

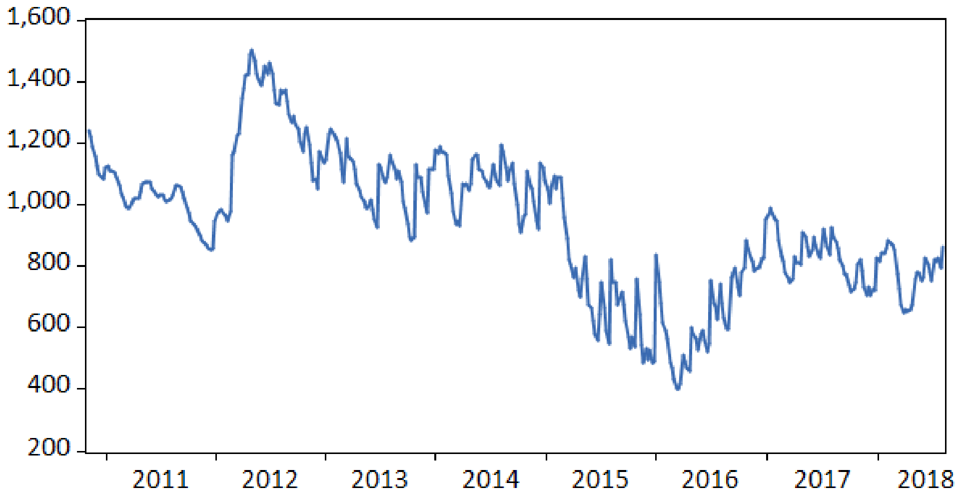
SSE decided on 1 January 1998 to be the basic period with the basic index of 1000 points for CCFI. Currently, 22 maritime companies which possess high market prestige and relatively significant market shares establish the panelists committee of CCFI (Shanghai Shipping Exchange, 2018). These panelists are;

i. CMA-CGM, China Ocean Shipping Company (COSCO) Shipping Lines, Evergreen Marine, Hamburg Süd, Hapag-Lloyd, K-line, Maersk, Mitsui OSK Lines (MOL), Mediterranean Shipping Company (MSC), Nippon Yusen Kaisha (NYK), Orient Overseas Container Line (OOCL), Pacific International Lines (PIL), Regional Container Lines (RCL), Shanghai Hai Hua Shipping, Shanghai Jin Jiang Shipping, Sinotrans Container Lines, SITC Container Lines, Yang Ming Marine Transport, Korea Marine Transport, Wan Hai Lines, TS Lines, ZIM Integrated Shipping Services.

1.1.2. Shanghai Containerized Freight Index (SCFI)

In order to satisfy the markets further need of another global liner shipping index and to optimize China's existing export liner shipping index system, at the date of 16 October 2009 SSE renovated and replaced its existing SCFI which was first issued on 7 December 2005. SSE took 16 October 2009 as its base period with the 1000 index points (Shanghai Shipping Exchange, 2018).

Figure 2: Shanghai Containerized Freight Index (SCFI)



Source: Processed by Author, Data from Bloomberg, 2018

1.1.2.1.Routes and Ports of Destination of SCFI

SCFI indicates the freight rates of Shanghai originated export container shipping market. It also has 13 sub-indices which at the end create the composite index. The index reflects both the actual freight rates and the seaborne surcharges applied of each of the shipping routes, located on the major liner shipping trade corridors from Shanghai to the; Europe, Mediterranean, United States West Coast (USWC), United States East Coast (USEC), Persian Gulf, West Africa, Australia/New Zealand, South Africa, South America, West Japan, Southeast Asia, East Japan, and Korea. The base ports defined for each individual trade routes as the ports of destination (Shanghai Shipping Exchange, 2018). Which are;

i. Europe — Rotterdam, Hamburg, Felixstowe, Antwerp, Le Havre
ii. Mediterranean — Valencia, Barcelona, Genoa, Naples
iii. USWC — Los Angeles, Oakland, Long Beach
iv. USEC — New York, Savannah, Charleston, Norfolk
v. West Japan — Osaka, Kobe
vi. East Japan — Tokyo, Yokohama
vii. Persian Gulf and Red Sea — Dubai
viii. Australia/New Zealand — Melbourne
ix. East/West Africa — Lagos
x. South Africa — Durban
xi. South America — Santos
xii. Southeast Asia — Singapore
xiii. Korea — Busan

1.1.2.2.Freight and Seaborne Surcharges of SCFI

The panelists report the rates which are defined by available booking prices given between the major container lines, shippers and freight forwarders, with a statistics concept known as “mode”. Type of the ship, age of the ship, volume of transport or the carrier does not affect the freight in this case. The unitization is United States Dollars/Twenty-foot Equivalent Unit (USD/TEU), except for USWC and USEC services which has the unitization method of United States Dollars/Forty-foot Equivalent Unit (USD/FEU). The index uses export CIF, CY-CY as the trade and transport terms (Shanghai Shipping Exchange, 2018). There are also various seaborne surcharges included in to calculation, which are;

i. Bunker Adjustment Factor (BAF)
ii. Fuel Adjustment Factor (FAF)
iii. Low Sulphur Surcharge (LSS)
iv. Emergency Bunker Surcharge (EBS)
v. Emergency Bunker Additional (EBA)

vi. Currency Adjustment Factor (CAF)
vii. Yen Appreciation Surcharge (YAS)
viii. Peak Season Surcharge(PSS)
ix. War Risk Surcharge(WRS)
x. Port Congestion Surcharge (PCS)
xi. Suez Canal Transit Fee/Surcharge (SCS)
xii. Suez Canal Fee (SCF)
xiii. Panama Transit Fee (PTF)
xiv. Panama Canal Charge (PCC).

It is imported to note that the Low Sulphur Surcharge (LSS) was started to be included from the end of year 2014.

1.1.2.3.Panelists and Freight Information of SCFI

SCFI provides the freight data from its panelists. All panel members are selected within the companies which possess high market prestige and relatively significant market shares in the maritime business. Currently, in addition to the 20 liner shipping companies, shipper and freight forwarders forming a group of 17 companies provide the freight information (Shanghai Shipping Exchange, 2018). They are:

i. Liner shipping panelists: Evergreen Marine, CMA-CGM, COSCO Shipping Lines, Hamburg Süd, K-Line, Maersk, MOL, NYK, OOCL, PIL, Hapag-Lloyd, RCL, SITC Container Lines, Shanghai Jin Jiang Shipping, Shanghai Hai Hua Shipping, Sinotrans Container Lines, Korea Marine Transport, Wan Hai Lines, TS Lines, Yang Ming Lines, MSC, and ZIM Lines.
ii. Freight forwarder or shipper panelists: China Ocean Shipping Company (COSCO) Logistics, Shanghai Asian Development International Transportation, JHJ International Transportation, Shanghai Jinchang Logistics, Orient International Logistics, Shanghai Huaxing International Container Freight Transportation, Shanghai Orient Express International Logistics, Shangtex Group International Logistics, Shanghai Richhood

International Logistics, Shanghai Viewtrans, SIPG Logistics, Shanghai Syntrans International Logistics, Sinotrans Eastern, Sunshine-Quick Group, Shanghai Sijin International Transportation, Shanghai Ba-Shi Yuexin Logistics Development, and UBI Logistics.

1.1.2.3.1. Calculation of Sub-Indices

The freight value belonging to a sub-index is calculated by finding the arithmetic mean of all reported freight rates for each specific route. It is also important to note that the minimum number of reports required weekly from each route is determined by the weighting of the route. At least five reports need to be received for the routes with less than 5% weighting percentage; for the routes with 5%-10% weighting the report requirement increases to at least six; for the routes with 10%-15% weighting the report requirement increases to at least seven; and lastly for the routes with more than 15% weighting the report requirement becomes at least eight per week (Shanghai Shipping Exchange, 2018). The equation of the individual freight calculation is;

$$P_t = \sum_{j=1}^{n} P_{ij} / n \tag{1.1}$$

Where i is route, j is sample company, and n is number of sample companies on specific route.

1.1.2.3.2. Calculation of Composite Index

The composite index is calculated by applying the weighted average method to all sub-indices. In this case the average container freight rate of a chosen route gets divided by average price of the base period for that route. The obtained result is multiplied by its weighting percentage and its base period index to determine the value for each route. Then the values of every sub-index gets added up to obtain the total index value (Shanghai Shipping Exchange, 2018).

$$I = \sum_{i=1}^{m} (P_i W_i / P_{i0}) * 1000 \quad (1.2)$$

Where i is route, m is number of the route, and W_i is the weighting of route i.

1.1.3. Ningbo Containerized Freight Index (NCFI)

NCFI is produced by Ningbo Shipping Exchange (NSE), a state-owned Chinese enterprise on 14 November 2011. Going forward from 23 October 2015, it is being sponsored by the Baltic Exchange and became the first outsourced index issued by the BE since 1744. The NCFI is published weekly to cover the movement of 20 feet, 40 feet and high cube containers. The composite index consists as a combination of three above mentioned container types and possesses four sub-indices. The NCFI is created with the data provided from the conducted transactions of panelists on NSE's own online trading platform (Kavussanos and Visvikis, 2016).

1.1.3.1. Routes and Destinations of NCFI

The four sub-indices forming the NCFI are established upon four specific routes and nine destinations. Each of these routes hold an important position on the liner shipping market, in which the shipping routes are the major container shipping corridors from Ningbo city of PRC to:

i. Europe (Ports of Hamburg and Rotterdam)
ii. East Mediterranean (Ports of Piraeus and Istanbul)
iii. Middle East (Ports of Dammam and Dubai)
iv. West Mediterranean (Ports of Barcelona, Valencia, and Genoa)

1.1.3.2. Freight and Seaborne Surcharges of NCFI

NCFI selects the data of the freight in the terms of export CIF and CY-CY. The freight contains basic freight and surcharges gathered from the panelists. The surcharges included in the reported freight rates are: BAF, LSS, EBS, CAF, YAS, PSS, FAF, WRS, PCC, PCS, SCS, SCF, EBA, PTF (Kavussanos and Visvikis, 2016).

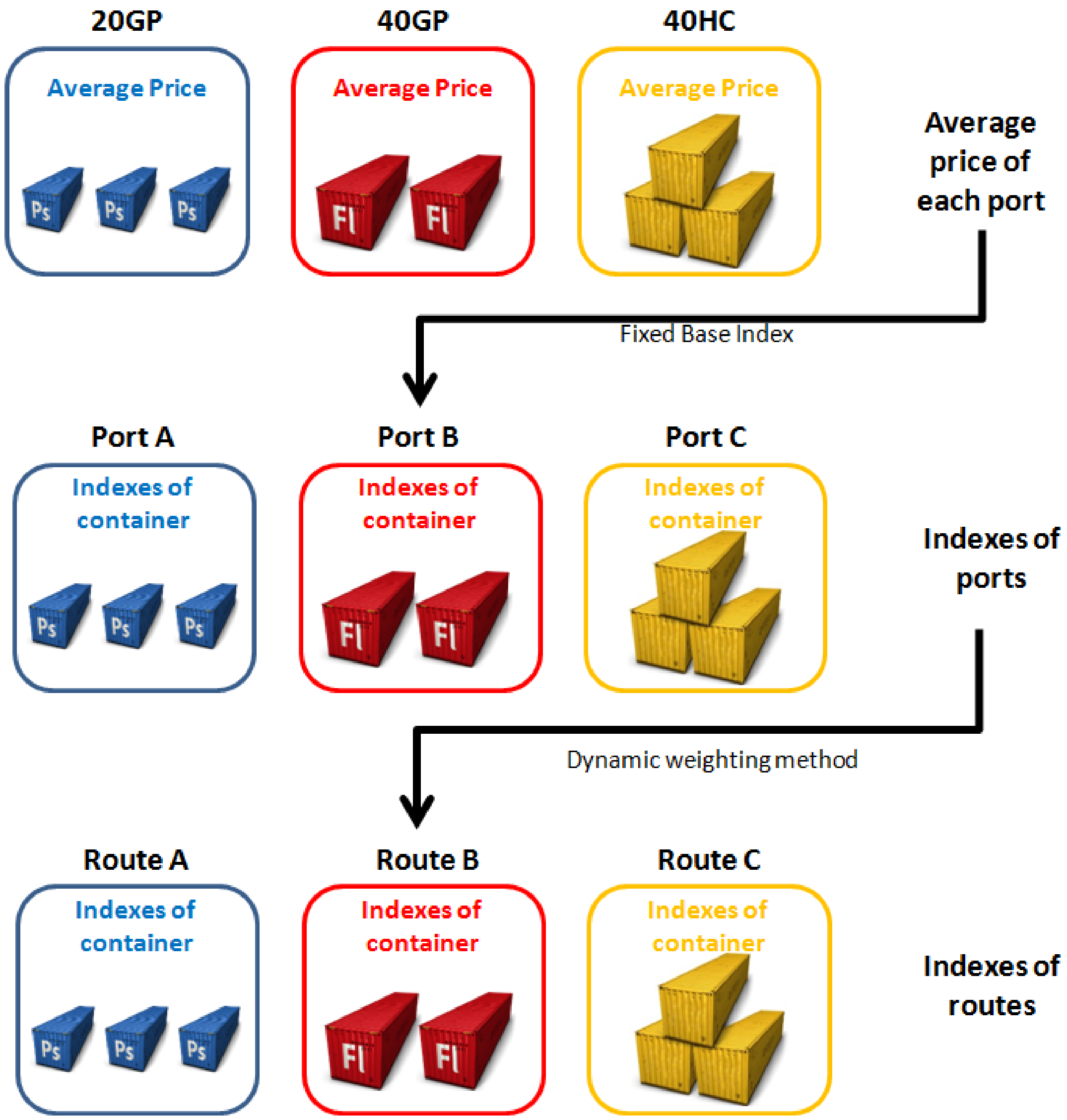
1.1.3.3. Panelists and Freight Information of NCFI

The panel members are leading freight forwarders which are actively operating on the reported routes and with considerable market shares in Ningbo. All of them trade on the Ningbo Exchange’s e-trading platform. These members are:

i. Consolidated Carriers Logistics (CCL)
ii. Headwin Logistics
iii. Ningbo E-Union Group
iv. Zhejiang Xinggang International Freight
v. Perfectever Logistics
vi. Ningbo Jet Express International Freight Forwarding
vii. Dashing International Logistics
viii. Huanji International
ix. De Well Group
x. Whale Logistics
xi. Sinotrans Ningbo Logistics

NCFI is created by the application of a classical price index model. The calculation methodology of NCFI and its sub-indices follows these steps: Firstly, the abnormal data is deleted by 3 Sigma Criteria. Abnormal data refers to the individual outlier data which would affect the calculation results in the process of index preparation. Secondly each type of container's average price of each port are calculated by the index calculation model. Then the indexes of container of each port are calculated by each type of container's average price and the basis average price of each port. Finally, the index of each route which is weighted for the volume on its representative trade gets calculated and it gets published (Kavussanos and Visvikis, 2016).

Figure 3: The Calculation Process of NCFI



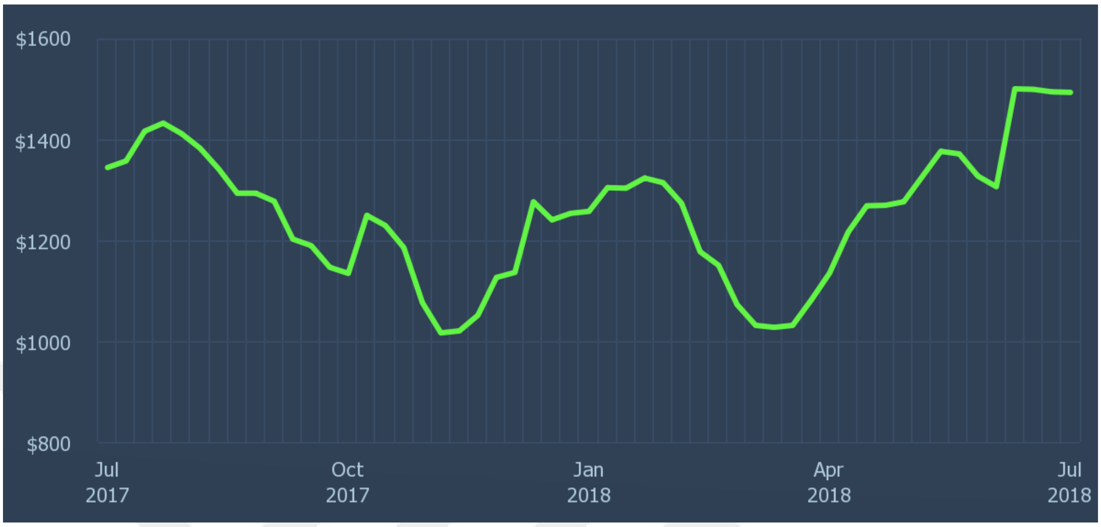
Source: Ningbo Shipping Exchange, 2018

Figure 3 above summarizes the layout and calculation process of NCFI, which got described in detail.

1.1.4. Freightos Baltic Global Container Index (FBX)

As for being the newest and one of the strongest entries to the container freight index genre, The Baltic Exchange audits a new index called Freightos Baltic Global Container Index (FBX) with the data supplied by Hong-Kong based digital container shipping platform Freightos. The foundation of the index is an overhaul of the Freightos' own Freightos International Freight Index (FFX) published in 2017.

Figure 4: Freightos Baltic Global Container Index (FBX)



Source: Freightos, 2018

FBX is published weekly on Sundays and represents the price of the previous week. Freightos already provides market intelligence and real-time freight booking and management for over 1000 carriers and forwarders, as well as over 3000 shippers. The data of FBX consists of the aggregation and anonymization of real-time freights of world-wide carriers, freight forwarders and shippers that offer services on Freightos platform (Freightos, 2018).

1.1.4.1. Routes and Destinations of FBX

The composite FBX is formed by taking the weighted averages of 12 sub-indices. All of the sub-includes include backhaul, with the exemption of both the South American routes. The routes forming sub-indices are:

i. China and Eastern Asia to USWC
ii. USWC to China and Eastern Asia
iii. China and Eastern Asia to USEC
iv. USEC to China and Eastern Asia
v. China and Eastern Asia to Northern Europe

vi. Northern Europe to China and Eastern Asia

vii. China and Eastern Asia to Mediterranean

viii. Mediterranean to China and Eastern Asia

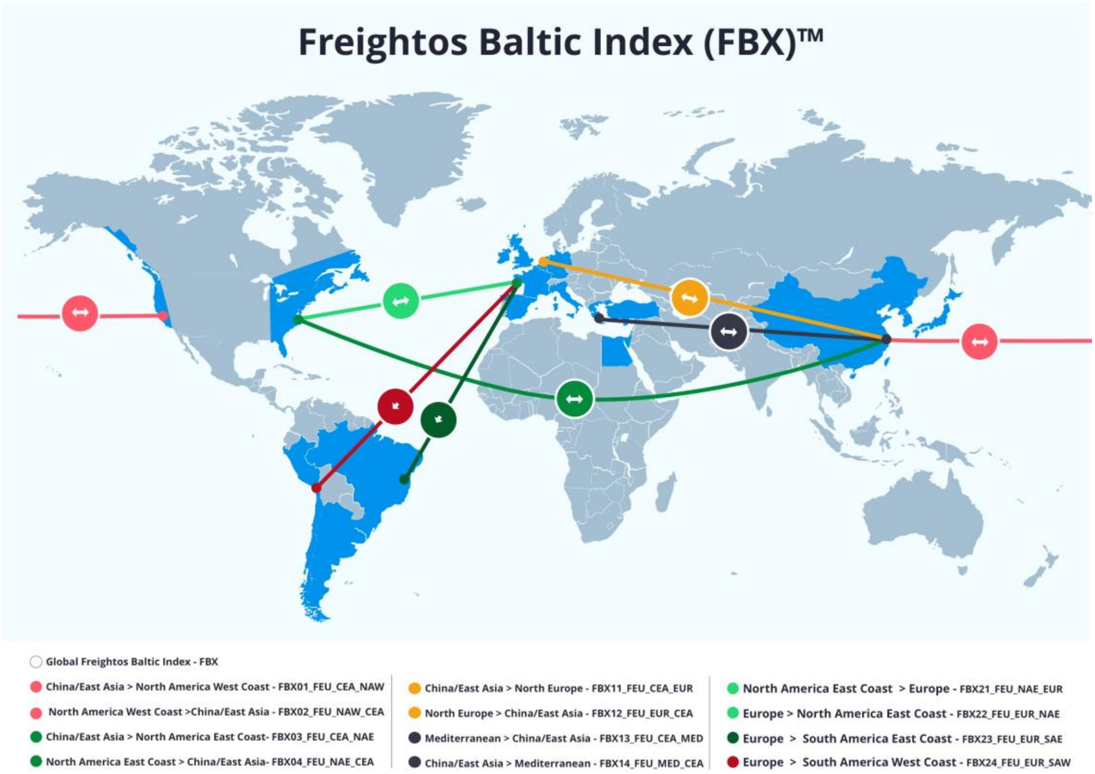
ix. USEC to Europe

x. Europe to NAEC

xi. Europe to South America East Coast

xii. Europe to South America West Coast

Figure 5: Routes of FBX



Source: Freightos, 2018

FBX also has a large number of representing port for each of the regions mentioned above. These representing ports are:

i. China and Eastern Asia Ports: Shanghai, Ningbo, Hong Kong, Shenzhen, Guangzhou, Kaohsiung, Tokyo, Busan

ii. USWC Ports: Long Beach, Los Angeles, Tacoma, Seattle, Oakland, Vancouver

iii. USEC Ports: Newark, New York, Savannah, Charleston, Montreal

iv. European Ports: Hamburg, Rotterdam, Felixstowe, Le Havre, Bremen, Antwerp, Southampton
v. Mediterranean Ports: Valencia, Algeciras, Barcelona, Port Said, Piraeus, Ambarli, Malta Freeport, Gioia Tauro, Genova, Ashdod
vi. South America East Coast Ports: Santos, Buenos Aires, Montevideo, Paranagua
vii. South America West Coast Ports: Callao, Guayaquil, San Antonio

1.1.4.2. Freight and Seaborne Surcharges of FBX

Freights used to calculate the index are in the form of Freight All Kind (FAK) tariffs circulating between freight forwarders, carriers and high-volume shippers. In order to get rid of the outlier influence, the calculation of index values are conducted on median of freight rates on active lanes with their corresponding weighting. Freightos monthly gathers 50-70 million freight data monthly. In addition to representing ocean freight prices, the FBX includes the following seaborne surcharges: BAF, CAF, SCS, PCS, PSS, WRS. Freightos also makes it so that the market intelligence on port and inland charges are available separately (Freightos, 2018).

Spot rates on container bookings represent around 25% of total bookings. In comparison to the contracted rates, these spot rates appear to possess much more volatility. That being said, it is important to note the markets shift towards the shorter contracts year by year. As in its core the FBX shows some notable differences from SCFI and other container freight indices. First of all, FBX uses aggregate and anonym data created by live transaction database which updates itself tens of millions of freight rates each week. Secondly the ever-growing database of Freightos provides more freight data points, which enables relatively higher accuracy. And lastly the FBX includes other major routes with backhauls, not just the routes originated from China (Freightos, 2018).

1.1.5. World Container Index (WCI)

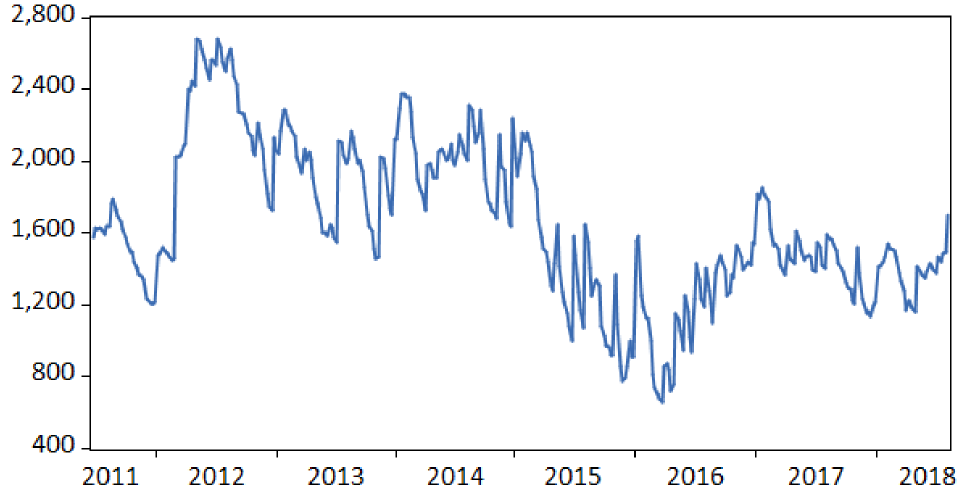
WCI is produced by Drewry Maritime Advisors in conjunction with Cleartrade Exchange. It reports sub-indices formed by agreed container freight rates on major trading routes connecting Eastern and Western markets as well as a composite index. The World Container Index is mainly designed for three main usages (Drewry, 2018):

i. Settling and Trading of Container Freight Derivative Contracts: With the provision of a finalized benchmark against which freight derivatives to trade and settle. This gives its users a notable forward discovery and freight risk management.

ii. Basis for Index Linked Container Contracts (ILCC): The WCI aims to satisfy the need for an independent and reliable source, which bases a mechanism for long-term freight contract volatility. It is a reasonable need from the market because long-term freight contracts can be designed in order to make the rates also fluctuate with the market movements.

iii. Benchmark Database for Freigt Rates and Historical Trends: One of the primary points led to creation of WCI is to create a large database of maritime business information which includes spot freight rates, historical rates and estimation of forward freight to all actors concerned in container shipping.

Figure 6: World Container Index (WCI)



Source: Processed by Author, Data from Bloomberg, 2018

The Figure 6 above illustrates flow of composite WCI from its first date of publication 23 June 2011 to 2 August 2018 on the weekly basis.

1.1.5.1. Routes and Sub-Indices of WCI

WCI consists of eight route-based sub-indices which represent the major East-West shipping routes and form the composite index. Drewry designed the WCI to provide an overall imagery of current situation and trend on its considered routes. These routes are:

i. Asia to Northern Europe (Shanghai – Rotterdam)
ii. Northern Europe to Asia (Rotterdam – Shanghai)
iii. Asia to Mediterranean (Shanghai – Genoa)
iv. Asia to USWC (Shanghai - Los Angeles)
v. USWC to Asia (Los Angeles – Shanghai)
vi. Asia to USEC (Shanghai - New York)
vii. USEC to Northern Europe (New York – Rotterdam)
viii. Northern Europe to USEC (Rotterdam - New York)

1.1.5.2. Panelists and Freight Information of WCI

Market agents such as shippers and forwarders from US, Asia and Europe submit detailed market assessments to WCI on freight rates given to them by container shipping carriers. Unlike other container shipping indices WCI does not receive information directly from carriers. To simply put, WCI evaluates carriers freight rates via carriers own customers, not direct from the carriers. As for the market reporters, the application of WCI does not disclose the identities of its panelists. This is mainly because WCI has agreed not to disclose the identities of its market reporters. Also having no information on who the WCI reporters are avoids the danger of manipulation of the index by a certain carrier which might agree upon an artificial freight rate with the reporters (Drewry, 2018).

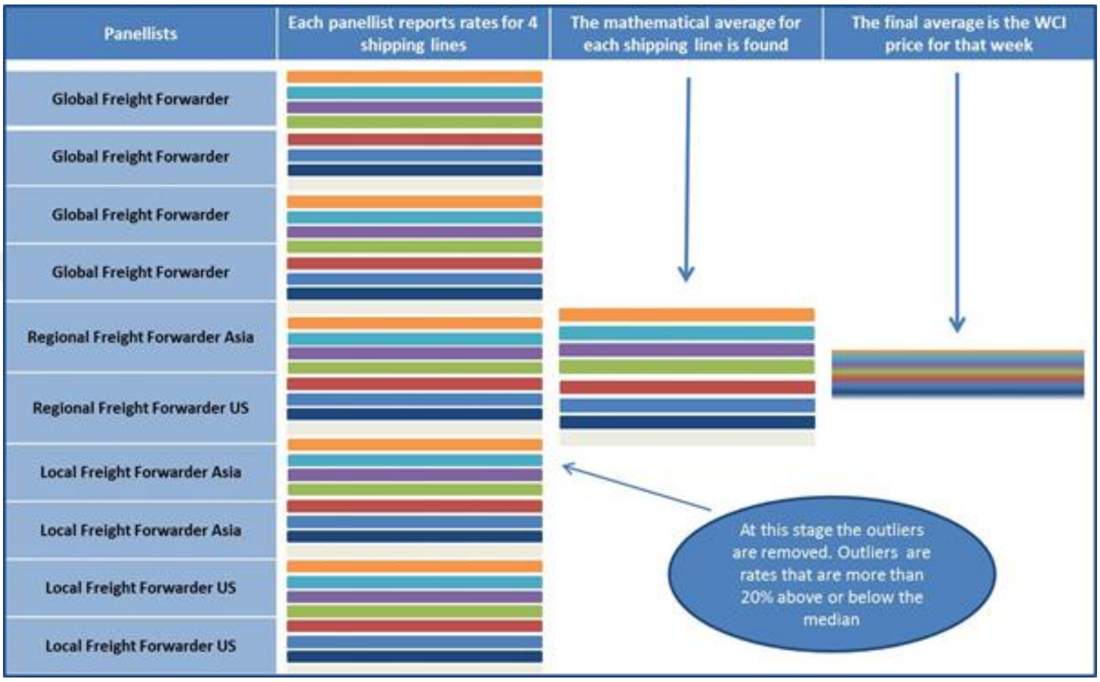
1.1.5.3. Freight and Seaborne Surcharges of WCI

Drewry Maritime Advisors use Freight All Kinds (FAK) rates because it can be a suitable benchmark for the general conditions of the market. FAK tariffs are not specific to a certain commodity or subject to special prices. All indexes are reported in USD/FEU. The used rates by the index are Container Yard to Container Yard (CY-CY) rates and the included surcharges are: BAF, EBS, CAF, PSS, Equipment Management Surcharge (EMS), Port Dues, Emergency Risk Surcharge (ERS), Carrier Security Charge (CSC), Port Security Charge (PSC), US Automated Manifest Fee, SCS, PTS, GAS, and PCS (Drewry, 2018).

1.1.5.4. Calculation of WCI

The panelists of WCI submit up to 4 market reports each week for each route they operate. In this case, each market report is for a freight which that panelist has contracted with a major container carrier. Then the market reports are calculated into the sub-indices with the following methodology on a per route basis. Firstly, the median of received freight rates are calculated. Then rates more than 20% higher or lower the median gets excluded from calculation. After the discarding the data, Drewry sorts the remaining freight rates for each of the inspected carriers. Then they report the average freight rate for every carrier separately. And lastly the average freight rates of all carriers are taken to form the final WCI freight for the calculated route for that specific week. Figure 7 below summarizes this calculation process.

Figure 7: Calculation Process of WCI



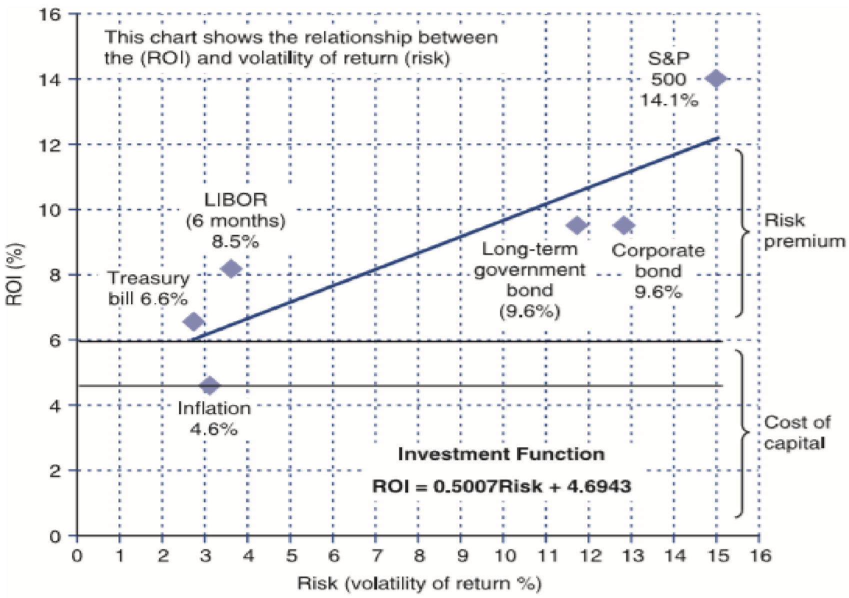
Source: Drewry, 2018

CHAPTER TWO
CHANGING VOLATILITY MODELS

Concepts such as uncertainty and risk reside in the center of theory of modern economics and also maritime economics. Due to shipping being a high capital intensive industry with large debt ratios, unpredictable earnings, blurred business structures; financing the shipping is challenging. Even if the financing situation is solved, the market volatility makes owners face serious problem of not being able to meet the debt payments with operating income (Stopford, 2009). This situation occurs because of a ship being a speculation, not just a transportation mean. During recessions a ship owner who funds with equity will be safe as long as the freight revenue covers the operating costs. On the other hand, a ship owner who funds with debts will face serious problems.

Stopford (2009) states that the combination of volatile earnings and low returns are the main distinguishing factor for shipping compared to other investments. He then employs a model which measures the risk by volatility, using the standard deviation of historical returns of various assets. This study results in average of 6% of Return on Investment (ROI) with 58% of return volatility for the shipping.

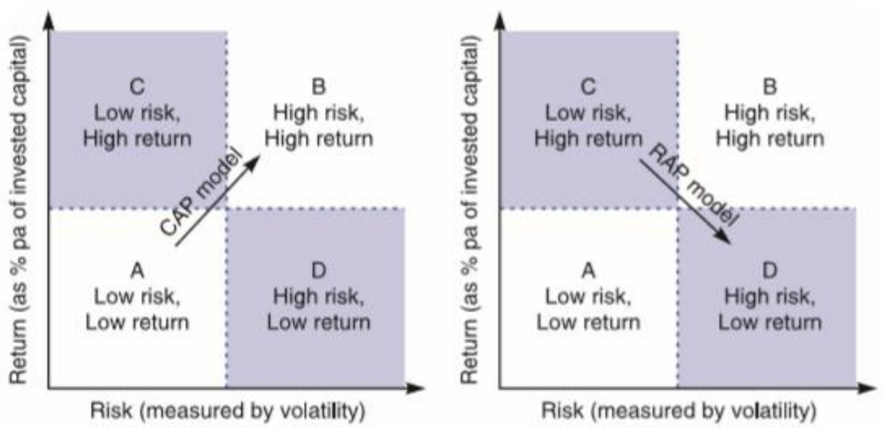
Figure 8. Risk Pricing of Various Assets



Source: Stopford, 2009.

When Figure 8 is examined in detail it can be seen that the shipping stands out with the lowest ROI and highest risk, which is so high it cannot come close to fit the graph among other assets, and contrast the expectation of higher returns on higher volatilities in Capital Asset Pricing (CAP) model. Then the question of why investing in shipping with much less returns than other assets and in much higher risk occurs. Although the perfect competition models answer this question for most shipping cases, it cannot fit for the container shipping due to product differentiation and much higher entry barriers. To provide more general fitting approach for liner market and shipping overall Stopford (2009) establishes a Risky Asset Pricing (RAP) model.

Figure 9. CAP and RAP Models



Source: Stopford, 2009.

In the CAP model, which is being widely used in traditional asset valuation, the institutional investors value the predictability offered by more stable investments. But in the RAP model, which explains the behavior of shipping markets, entrepreneurs value the opportunities offered by volatile investments. This points out the attraction of the shipping markets highly volatile and cyclical characteristics to the shipping entrepreneurs. Which due to these wild fluctuations and cycle behaviors, the invested high-risk low return situation of D might result in a spiking high returns every once in a while. That being said the most usual case for shipping is the low risk-high return situation of C. This situation occurs when they charter the vessel or make slot agreements for long period of times to give up the flexibility and volatility and demands more returns as a compensation for this situation, thus resulting in high returns with much lower risks Stopford (2009).

In an econometrical and more general manner of speaking, heteroscedasticity is considered as a problem for cross-sectional data, but it was observed that variance of the error term could change in time in econometrics models aiming to estimate financial time series such as stock prices, freight indices, interest and exchange rates. Also, in traditional time series models there is an assumption that variance of the error terms does not change in time.

When a Heteroscedasticity problem occurs in a traditional time series model, Ordinary Least Squares (OLS) or Maximum Likelihood (ML) estimator preserves its unbiasedness and consistency properties. Still, when a model consists of heteroscedasticity it can lose its efficiency, and because of that the parameter estimations might turn out to be statistically insignificant. To address the above-mentioned issue, certain models were proposed that allow the changes in variance and covariance in time. By associating the variance of current error term with the squared values of the previous error terms, Engle (1982) proposed the ARCH model.

2.1. CONDITIONAL AND UNCONDITIONAL ESTIMATION

Unconditional volatility often means that the mean of the volatility for an observed period (Hayashi, 2000). This is a direct approach which is useful if return of previous period cannot be observed. Because if the previous periods volatility cannot be determined, the best chance to estimate the volatility of next period would be the taking a mean for the entire period, thus taking an unconditional volatility approach. Unfortunately, with this approach volatility clustering does not taken into consideration by the model (Brooks, 2014).

On the other hand, the conditional volatility estimators adjoin available information at each period. Which means in order to make a conditional volatility estimation, volatility for each period must be observed (Hayashi, 2000). The literal meaning of the conditional in the model means that the models condition is to know previous periods volatility (Brooks, 2014).

As a result, it can be said that the unconditional estimation is less efficient than conditional estimation because of the volatility clustering. The conditional estimations take volatility clustering into consideration by adjoining the information available at each period; therefore, the two methods do not result in the exact the same way (Campbell et al, 1998). The most popular and heavily practiced upon models for estimation conditional variance are the ARCH(p) and GARCH(p,q) models (Hayashi, 2000).

2.1.1. Autoregressive Conditional Heteroscedasticity (ARCH) Models

Based on the existence of volatility clustering, Engle (1982) proposed the ARCH model. This was etched in the history as the first model which allowed the estimation of conditional volatility in a relatively accessible manner. The main idea behind the model, and what made it unique at that time is that the model does not variance as a constant (Engle, 1982).

The ARCH model allows the error variance to change as a function of the squares of the previous error terms by abandoning the constant variance assumption in the traditional time series models. A way of modeling the fluctuation encountered in time series is undertaken by defining an independent variable related to volatility and predicting the volatility via this variable (Engle, 1982). The equation below represents a simple example to modeling volatility through an independent variable.

$$y_{t+1} = \varepsilon_{t+1} x_t \tag{2.1}$$

In this equation, ε_{t+1} is the pure error term which has variance of σ^2 and x_t is described as the independent variable. If x is a time independent constant value, series y_t becomes a white noise process with constant variance. With that, the conditional variance of y_{t+1} given below, cannot be independent from the realized value of x_t.

$$Var\langle y_{t+1} | x_t \rangle = x_t^2 \sigma^2 \tag{2.2}$$

In this case, the greater x_t is, the greater the conditional variance of y_{t+1} becomes. In addition to that, if the consecutive values of series x_t have positive internal correlation, series y_t will be positively internally correlated as well. With this situation the series x_t will help describing the volatility of series y_t. But this approach can be criticized for its assumption of a specific reason for heteroskedasticity. Because it is not always possible to choose between a number of plausible candidates and to associate the volatility of the related variable with only the chosen independent variable (Engle, 1982).

In order to prevent the above mentioned issue Engle (1982) proved the possibility of modelling the mean and variance of any series simultaneously. In order to reach an ARCH model a stationary autoregressive model such as;

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \varepsilon_t \tag{2.3}$$

is estimated. In this case the conditional estimation of y_{t+1} becomes;

$$E_t(y_{t+1}) = \alpha_0 + \alpha_1 y_t \tag{2.4}$$

If this conditional mean is used to estimate y_{t+1}, the variance of estimation error becomes;

$$E_t\lfloor(y_{t+1} - \alpha_0 - \alpha_1 y_t)^2\rfloor = E_t(\varepsilon_{t+1}^2) = \sigma^2 \tag{2.5}$$

Also the unconditional estimation and variance of y_{t+1} is represented in order like;

$$E(y_{t+1}) = \alpha_0/(1-\alpha_1) \tag{2.6}$$

$$\begin{aligned} E\{[y_{t+1} - \alpha_0/(1-\alpha_1)]^2\} &= E\lfloor(\varepsilon_{t+1}\alpha_1\varepsilon_t + \alpha_1^2\varepsilon_{t-1}^2 + \cdots)^2\rfloor \\ &= \sigma^2/(1-\alpha_1^2) \end{aligned} \tag{2.7}$$

As seen from the equations above, the unconditional estimation possesses greater variance than conditional estimation. Because of its consideration of current period and known past period information, conditional estimation has a smaller variance therefore making it more preferable.

Similarly, if variance of the series $\{\varepsilon_t\}$ is not constant, ARMA type models can be used in order to estimate continuous movement of variance in a certain direction. For example if $\{\hat{\varepsilon}_t\}$ is the residual series of the model;

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \varepsilon_t \tag{2.8}$$

Then the conditional variance of y_{t-1} is;

$$Var\langle y_{t+1}|y_t\rangle = E_t\lfloor(y_{t+1} - \alpha_0 - \alpha_1 y_t)^2\rfloor = E_t\varepsilon_{t+1}^2 \tag{2.9}$$

At this point, it is required to construct a model which possesses the conditional variance at Equation (2.8) that is inconstant and time varying. For this matter, modeling the conditional variance as an AR(p) process using the squares of estimated residuals is considered as a valid approach. Squares of estimated residuals can be represented as an AR(p) process and v_t being a white noise process like;

$$\hat{\varepsilon}_t^2 = \alpha_0 + \alpha_1\hat{\varepsilon}_{t-1}^2 + \alpha_2\hat{\varepsilon}_{t-2}^2 + \cdots + \alpha_p\hat{\varepsilon}_{t-p}^2 + v_t \tag{2.10}$$

If all the parameters in the model except the constant would be zero, the estimated variance would be equal to α_0 constant value. In other cases the conditional variance of y_t will be estimated in respect of the autoregressive process at Equation (2.10). For this case, the conditional variance of next period can be estimated using an autoregressive process such as;

$$E_t\hat{\varepsilon}_{t+1}^2 = \alpha_0 + \alpha_1\hat{\varepsilon}_t^2 + \alpha_2\hat{\varepsilon}_{t-1}^2 + \cdots + \alpha_p\hat{\varepsilon}_{t-1-p}^2 \tag{2.11}$$

Therefore, Equation (2.10) can be describes as an ARCH(p) model.

Realistically, rather than modeling v_t linearly like in Equation (2.10), modeling it as a multiplicative error term results in a much more easily examinable structure. Engle (1982) proposed a simple equation of;

$$\varepsilon_t = v_t \sqrt{\alpha_0 + \alpha_1 \varepsilon_{t-1}^2} \tag{2.12}$$

to give an example of multiplicative conditional heteroscedasticity models. In this model, v_t and ε_{t-1} is independent form each other and, v_t is described as a white noise process with its variance equals to one. Also α_0 and α_1 has constant values under the constraints of $\alpha_0 > 0$ and $0 < \alpha_1 < 1$.

When the properties of series $\{\varepsilon_t\}$ are examined, it can be seen that the each component of the series $\{\varepsilon_t\}$ has zero mean and intrinsic because of v_t being a pure error term and independent of ε_{t-1}. Because of $Ev_t = 0$, the unconditional expectation of ε_t becomes;

$$E\varepsilon_t = E\left\lfloor v_t(\alpha_0 + \alpha_1 \varepsilon_{t-1}^2)^{\frac{1}{2}}\right\rfloor = Ev_t E(\alpha_0 + \alpha_1 \varepsilon_{t-1}^2)^{\frac{1}{2}} = 0 \tag{2.13}$$

Similarly the unconditional variance of ε_t can be calculated with;

$$E\varepsilon_t^2 = E\lfloor v_t^2(\alpha_0 + \alpha_1 \varepsilon_{t-1}^2)\rfloor = Ev_t^2 E(\alpha_0 + \alpha_1 \varepsilon_{t-1}^2) \tag{2.14}$$

In this case because of the variance of v_t equals to one and unconditional variances of ε_t and ε_{t-1} are equal, the unconditional variance can be calculated with;

$$E\varepsilon_t^2 = \alpha_0/(1-\alpha_1) \tag{2.15}$$

Because of this, unconditional mean and the variance possesses constant values and do not be affected by error process. Also because of v_t and ε_{t-1} being independent of each other and the expected value of v_t equals to zero, the conditional value of ε_t also gets the value of zero.

$$E\langle \varepsilon_t | \varepsilon_{t-1}, \varepsilon_{t-2}, \dots \rangle = E v_t E(\alpha_0 + \alpha_1 \varepsilon_{t-1}^2)^{\frac{1}{2}} = 0 \tag{2.16}$$

With that, the conditional variance of ε_t no longer stays as a constant value and becomes dependent on one previous periods realized value. And with the variance of v_t equals to one, the conditional variance of ε_t is calculated with;

$$E\langle \varepsilon_t^2 | \varepsilon_{t-1}, \varepsilon_{t-2}, \dots \rangle = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 \tag{2.17}$$

The conditional variance at Equation (2.16) follows a first order autoregressive process. To prevent the conditional variance from taking negative values, it is required to constraint the coefficients α_0 and α_1. Therefore, the coefficients α_0 and α_1 has to be positive. Also, in order to achieve stationarity of the autoregressive process, α_1 coefficient has to be constrained to maintain the $0 < \alpha_1 < 1$ inequality.

As a result, ARCH models possess an error structure which has both conditional and unconditional means are equal to zero. In addition to that, despite the series $\{\varepsilon_t\}$ not being interrelated, the error terms are not independent of each other because of them being related via their second moments. In this case, conditional variance itself is an autoregressive process caused by the conditional heteroscedastic errors. Therefore, greater the absolute realized value of error term it gets from zero, greater the conditional variance of ε_t has to become. At this point it is important to examine how the error structure of Equation (2.12) affects the series $\{y_t\}$. Defining a series $\{y_t\}$ such as;

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \varepsilon_t \tag{2.18}$$

And its conditional mean and variance can be written in order;

$$E_{t-1} y_t = \alpha_0 + \alpha_1 y_{t-1} \tag{2.19}$$

$$\begin{aligned} Var\langle y_t | y_{t-1}, y_{t-2}, \dots \rangle &= E_{t-1}(y_t - \alpha_0 - \alpha_1 y_{t-1})^2 = E_{t-1}(\varepsilon_t)^2 \\ &= \alpha_0 + \alpha_1 (\varepsilon_{t-1})^2 \end{aligned} \tag{2.20}$$

Because of α_1 and ε_{t-1}^2 cannot obtain negative values, the conditional variance of y_t cannot become less than α_0. Therefore, for non-zero values of ε_{t-1} the conditional variance of y_t is positively correlated with α_1 coefficient.

When the Equation (2.17) is solved and its expected value is taken, the equation below is obtained;

$$y_t = \alpha_0/(1-\alpha_1) + \sum_{i=0}^{\infty} \alpha_1^i \, \varepsilon_{t-i} \tag{2.21}$$

Because of the expected value of ε_t is zero for all the t values, the unconditional expectation of y_t becomes;

$$Ey_t = \alpha_0/(1-\alpha_1) \tag{2.22}$$

As for all the i values result in $E\varepsilon_t\varepsilon_{t-i} = 0$, the unconditional variance of y_t can be obtained with;

$$Var(y_t) = \sum_{i=0}^{\infty} \alpha_1^{2i} \, var(\varepsilon_{t-i}) \tag{2.23}$$

Considering the unconditional variance of ε_t being constant, we can reach the expression of;

$$Var(y_t) = [\alpha_0/(1-\alpha_1)][1/(1-\alpha_1^2)] \tag{2.24}$$

It can be clearly seen that the variance of series $\{y_t\}$ is in an increasing relation with the absolute values of the parameters α_1 and α_1. Therefore, the ARCH methodology comes forward as an eligible method for modeling the volatility, which has its error term observed in multiple periods, in a univariate structure.

2.1.1.1. ARCH(p) Model

In the linear ARCH(p) model, the conditional variance is displayed as a linear function of previous periods squared error terms like (Engle, 1982);

$$R_t = X_1\delta + \varepsilon_t \tag{2.25}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2 \tag{2.26}$$

In the model, Equation (2.25) represents the mean equation and Equation (2.26) represents the variance equation. So, for this model to be defined and for conditional variance to be positive, the parameters in the model should comply with the constraints $\omega > 0$ and $\alpha_1 \geq 0, \dots, \alpha_p \geq 0$.

The ARCH(p) model at the Equation (2.26) can be written under the $v_t \equiv \omega + \varepsilon_t^2 - \sigma^2$ definition like;

$$\varepsilon_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2 + v_t \tag{2.27}$$

For this, because of $E_{t-1}(v_t) = 0$ the model essentially coincides as an AR(p) model which includes squared error terms. In this case the unconditional variance becomes;

$$Var(\varepsilon_t) = \sigma^2 = \omega/(1 - \alpha_1 - \cdots - \alpha_p) \tag{2.28}$$

Therefore, the covariance of the autoregressive conditional variance process will only be stationary if the sum of positive autoregressive parameters be less than one.

In an ARCH process, it can be clearly seen that the error terms are not independent through time, even though they may not be interrelated. Therefore, conditional variance of the error term in an ARCH(p) model, is indeed an increasing function of magnitudes of previous error terms in absolute values. Simply put, regardless of their signs greater errors are followed by greater errors and smaller errors are followed by smaller ones.

On the other hand, if we assume the standardized errors at the mean equation are time independent, the unconditional distribution of ε_t will have fatter tails than the distribution of v_t . For example, for an ARCH(1) model which possesses conditionally normally distributed error terms, when $3\alpha_1^2 < 1$ the kurtosis of the error term distribution can be calculated with;

$$E(\varepsilon_t^4)/E(\varepsilon_t^2)^2 = 3(1-\alpha_1^2)/(1-3\alpha_1^2) \quad (2.29)$$

When $3\alpha_1^2 \geq 1$, the kurtosis of the error term distribution will be;

$$E(\varepsilon_t^4)/E(\varepsilon_t^2)^2 = \infty \quad (2.30)$$

In both cases, both of them will result in a higher value than 3, which is the value of the kurtosis in a normal distribution function.

2.1.1.2. Weaknesses of the ARCH Model

Although ARCH models suggest a parametric structure which can catch numerous empirical indications and estimate volatility in this framework, possesses certain weaknesses (Tsay, 1986). Theses weaknesses are:

i. Because of the shocks from previous periods included in the model are squared, it presumes both positive and negative shocks have the same effect on the volatility. It is known for a fact that financial asset values can react asymmetrically to positive and negative shocks.
ii. Coefficients in the ARCH model are subject to very strict constraints.
iii. The ARCH model does not contribute to understanding the changes in financial time series, it only proposes a mechanical way of determining the way conditional variance behaves.

iv. Because of ARCH models react slowly to the large shocks coming into the financial returns, it can overestimate the volatility of financial time series.

2.1.1.3. Estimation of ARCH Model

Under the assumption of normal distribution, $\alpha = (\omega, \alpha_1, \dots, \alpha_m)$ and $f\langle \varepsilon_1, \dots \varepsilon_p | \alpha \rangle$ being the common likelihood distribution function, the likelihood function of any ARCH(p) model can be expressed as;

$$f\langle \varepsilon_1, \dots \varepsilon_T | \alpha \rangle = \prod_{t=p+1}^{T} \frac{1}{\sqrt{2\pi\sigma_t^2}} \exp[-\frac{\varepsilon_t^2}{2\sigma_t^2}] \\ x f\langle \varepsilon_1, \dots \varepsilon_p | \alpha \rangle \tag{2.31}$$

When the sample is large enough, $f\langle \varepsilon_1, \dots \varepsilon_p | \alpha \rangle$ can be excluded from the likelihood function to convert the conditional probability function into;

$$f\langle \varepsilon_{p+1}, \dots \varepsilon_T \big| \alpha, \varepsilon_1, \dots \varepsilon_p \rangle = \prod_{t=p+1}^{T} \frac{1}{\sqrt{2\pi\sigma_t^2}} \exp[-\frac{\varepsilon_t^2}{2\sigma_t^2}] \tag{2.32}$$

When the natural logarithm of conditional likelihood function is taken in order to maximize it, the following log-likelihood function is obtained;

$$\ell\langle \varepsilon_{p+1}, \dots \varepsilon_T \big| \alpha, \varepsilon_1, \dots \varepsilon_p \rangle = \sum_{t=p+1}^{T} -\frac{1}{2}\ln(2\pi) - \frac{1}{2}\ln(\sigma_t^2) - \frac{\varepsilon_t^2}{2\sigma_t^2} \tag{2.33}$$

Because of the first term of this function does not have a parameter, the likelihood function becomes;

$$\ell\langle \varepsilon_{p+1}, \dots \varepsilon_T \big| \alpha, \varepsilon_1, \dots \varepsilon_p \rangle = -\sum_{t=p+1}^{T} \left[\frac{1}{2}\ln(\sigma_t^2) + \frac{\varepsilon_t^2}{2\sigma_t^2}\right] \tag{2.34}$$

In some cases, assuming the t-distribution for v_t, which has fatter tails than normal distribution might give more accurate results. When x_φ is assumed as a t distribution with the φ degrees of freedom, for $\varphi > 2$, it can be said that $Var(x_\varphi) = \varphi/(\varphi - 2)$.

For $\Gamma(x)$ Gamma function and $\varphi > 2$, when defined as $v_t = \frac{x_\phi}{\sqrt{\phi/(\phi-2)}}$, the probability density function of v_t becomes;

$$f\langle v_t|\phi\rangle = \frac{\Gamma\left(\frac{(\phi+1)}{2}\right)}{\Gamma\left(\frac{\phi}{2}\right)\sqrt{(\phi-2)\pi}}\left(1+\frac{v_t^2}{\phi-2}\right)^{-(\phi+1)/2} \tag{2.35}$$

Because of $\varepsilon_t = \sigma_t v_t$ and $A_p = (\varepsilon_1, \varepsilon_2, \dots, \varepsilon_p)$, the conditional likelihood function of ε_t can be described as;

$$f\langle \varepsilon_{p+1}, \dots \varepsilon_T \big| \alpha, A_p\rangle = \prod_{t=p+1}^{T} \frac{\Gamma\left(\frac{(\phi+1)}{2}\right)}{\Gamma\left(\frac{\phi}{2}\right)\sqrt{(\phi-2)\pi}} \frac{1}{\sigma_t}\left[1+\frac{\varepsilon_t^2}{(\phi-2)\sigma_t^2}\right]^{-\frac{(\phi+1)}{2}} \tag{2.36}$$

If the degrees of freedom of the t distribution is predetermined, then the conditional log-likelihood potion becomes;

$$\ell\langle \varepsilon_{p+1}, \dots \varepsilon_T \big| \alpha, A_p\rangle = -\sum_{t=p+1}^{T}\left[\frac{\phi+1}{2} ln\left(1+\frac{\varepsilon_t^2}{(\phi-2)\sigma_t^2}\right)+\frac{1}{2} ln(\sigma_t^2)\right] \tag{2.37}$$

2.1.2. Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model

In the empirical applications of ARCH(p) model it is possible to lags to venture deep. Because of this reason it might be required to estimate very large number of parameters (Brooks, 2014). To prevent this inconvenience Bollerslev (1986) proposed the GARCH model.

In this framework the GARCH(p,q) model is defined as;

$$R_t = X_t\delta + \varepsilon_t \tag{2.38}$$

$$\varepsilon_t = \sigma_t v_t \tag{2.39}$$

In this definition v_t represents the white noise process which has zero mean and its variance equals to one, and the lagged values of v_t and ε_t are considered independent of each other. For this model the conditional variance is defined as;

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \equiv \omega + \alpha(L)\varepsilon_{t-1}^2 + \beta(L)\,\sigma_{t-1}^2 \tag{2.40}$$

In order to conditional variance in the GARCH(p,q) to be defined, the constraints $\omega > 0$, $\alpha_i \geq 0$, $\beta_i \geq 0$, and $\sum_{i=1}^{\max(q,p)}(\alpha_i + \beta_i) < 1$ has to be provided. The last of the constraints indicates that the unconditional variance of ε_t is finite, and its conditional variance is time varying. In order to understand the properties of GARCH model, the definition of $\eta_t = \varepsilon_t^2 - \sigma_t^2$ is made to recompose the Equation (2.40) in the form of;

$$\varepsilon_t^2 = \omega + \sum_{i=1}^{\max(p,q)} (\alpha_i + \beta_i)\varepsilon_{t-i}^2 + \eta_t - \sum_{j=1}^{q} \beta_j \eta_{t-j} \tag{2.41}$$

This equation implies an ARMA structure for ε_t^2. By using the unconditional mean of ARMA model, the equation below can be obtained;

$$E(\varepsilon_t^2) = \frac{\mu}{1 - \sum_{i=1}^{\max(p,q)}(\alpha_i + \beta_i)} \tag{2.42}$$

By focusing on the simplest GARCH model, which is GARCH(1,1) we can easily examine the strengths and weaknesses of this methodology. Under the constraints of $\alpha_1 \geq 0$, $\beta_1 \leq 1$, and $(\alpha_i + \beta_i) < 1$ the variance equation of GARCH(1,1) model is expressed as;

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{2.43}$$

Firstly it can be said that greater the ε_{t-1}^2 and σ_{t-1}^2 gets, greater the σ_t^2 will become. That implies the volatility clustering, which is one of the main properties examined in financial time series.

Secondly, when $1 - 2\alpha_1^2 - (\alpha_1 + \beta_1)^2 > 0$ the following equation, which shows just like in ARCH models the distribution of error term in GARCH(1,1) model possesses fatter tails than normal distribution;

$$\frac{E(\varepsilon_t^4)}{[E(\varepsilon_t^2)]^2} = \frac{3[1 - (\alpha_1 + \beta_1)^2]}{1 - (\alpha_1 + \beta_1)^2 - 2\alpha_1^2} > 3 \tag{2.44}$$

Thirdly, the model provides a simple parametric function which shows the changes in volatility over time. In this case the GARCH model is preferred over the ARCH model for its consistency over parameters.

The GARCH model estimation can be made with a similar methodology with ARMA model. For example, the forecast of GARCH(1,1) model for the next period is;

$$\sigma_h^2(1) = \omega + \alpha_1 \varepsilon_h^2 + \beta_1 \sigma_h^2 \tag{2.45}$$

Then the forecast of the model for l periods later becomes;

$$\sigma_h^2(l) = \frac{\omega[1 - (\alpha_1 + \beta_1)^{l-1}]}{1 - \alpha_1 - \beta_1} + (\alpha_1 + \beta_1)^{l-1} \sigma_h^2(1) \tag{2.46}$$

Under the constraint of $(\alpha_1 + \beta_1) < 1$, the conditional variance of GARCH(1,1) model converges the models unconditional variance when its forecasting horizon is infinite because of the equation below;

$$\lim_{l \to \infty} \sigma_h^2(l) = \frac{\mu}{1 - \alpha_1 - \beta_1} \tag{2.47}$$

With the addition of exogenous or predetermined variables, the GARCH(p,q) model can also be constructed like;

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \kappa_t \pi \tag{2.48}$$

2.1.3. Extensions to the ARCH/GARCH Models

In order to eliminate the weaknesses of and improve upon the basic ARCH and GARCH models, many researches came up with extensions and modifications to those models over the years. The most notable univariate models being ARCH-M, IGARCH, EGARCH, TGARCH, and PGARCH will be discussed in detail at this section.

2.1.3.1. Autoregressive Conditional Heteroscedasticity in Mean (ARCH-M) Model

The theory of finance claims that there is clearly a positive relationship between the expected returns and variance (Fama and Miller, 1972). Engle et al (1987) proposed the ARCH-M model to take this relationship into account, which includes the conditional variance or standard deviation as an explanatory variable to the mean equation. This model is mainly employed in financial applications, in which the expected financial asset returns are related with that same assets expected risk. As φ being the expected risk coefficient, is evaluated as a criterion for the risk-return relationship. Therefore, the ARCH-M model is expressed as;

$$R_t = X_t\delta + \phi\sigma_t^2 + \varepsilon_t \tag{2.49}$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{2.50}$$

The natural logarithms of conditional standard deviation and conditional heteroscedasticity are included to the mean equation of the model in order to complete the process.

$$R_t = X_t\delta + \phi\sigma_t + \varepsilon_t \tag{2.51}$$

$$R_t = X_t\delta + \phi log(\sigma_t^2) + \varepsilon_t \tag{2.52}$$

2.1.3.2. Integrated Generalized Autoregressive Conditional Heteroscedasticity (IGARCH) Model

When the GARCH(p,q) model is rearranged just like in Equation (2.27), it can be expressed as;

$$\varepsilon_t^2 = \omega + [\alpha(L) + \beta(L)]\varepsilon_{t-1}^2 - \beta(L)v_{t-1} + v_t \tag{2.53}$$

This equation actually describes an ARMA(max(p,q), p) for ε_t^2. This models covariance stationarity is strictly dependent on the roots of the $\alpha(x) + \beta(x) = 1$ polynomial to being outside of the unit circle. In most empirical applications on high frequency financial data, the summation of $\alpha(1) + \beta(1)$ equates very close to one. This situation laid out the empirical framework for Engle and Bollerslev (1986) to develop the model called Integrated GARCH (IGARCH). Because of $[\alpha(L) + \beta(L)]$ polynomial possess a unit root in IGARCH type models, a shock applied on the conditional variance becomes permanent and makes itself an important factor to be considered in making forecasts for a long time.

2.1.3.3. Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) Model

As it was discussed in the previous sections, the GARCH model does a remarkable job on successfully catching the empirical findings, such as volatility clustering and fat tails in financial asset returns. With that, GARCH process falls short on captivating the asymmetry of the variance structure because it describes the conditional variance as the function of the error term magnitudes, regardless of their positivity or negativity. To improve this condition Nelson (1991) developed the EGARCH model for asymmetry of the volatility structure to be taken into account. There are various ways to express the conditional variance equation for EGARCH model, such one expression is;

$$ln(\sigma_t^2) = \omega + \beta\, ln(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \tag{2.54}$$

The asymmetry of the volatility structure can be easily observed if the γ appears statistically significant.

2.1.3.4. Threshold Generalized Autoregressive Conditional Heteroscedasticity (TGARCH) Model

As for being another model taking asymmetric effects into account, the conditional variance equation is expressed as;

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \gamma_i S_{t-i} \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \varepsilon_{t-j}^2 \tag{2.55}$$

where,

$$S_{t-i} = \begin{Bmatrix} 1\ if\ \varepsilon_{t-i} < 0 \\ 0\ if\ \varepsilon_{t-i} \geq 0 \end{Bmatrix} \tag{2.56}$$

The model suggests that, depending on whether the ε_{t-i} is above or below the threshold value of zero, ε_{t-i}^2 can have different effects on the conditional variance. When ε_{t-i} is positive, the conditional impact of ε_{t-i}^2 on conditional variance is $\alpha_i\varepsilon_{t-i}^2$; when ε_{t-i} is negative, the impact of ε_{t-i}^2 is $(\alpha_i + \gamma_i)\varepsilon_{t-i}^2$. TGARCH model was proposed by Zakoian (1994) to explain the asymmetry in volatility structure in this manner.

2.1.3.5. Power Generalized Autoregressive Conditional Heteroscedasticity (PGARCH) Model

In order to catch the volatility clustering phenomenon, Taylor (1986) and Schwert (1989) modeled the conditional standard deviation as a distribution of absolute lagged values of error terms such as;

$$\sigma_t = \omega + \sum_{i=1}^{p} \alpha_i |\varepsilon_{t-i}| + \sum_{j=1}^{q} \beta_j \sigma_{t-j} \tag{2.57}$$

This and some other similar models were generalized by Ding et al (1993) and named PGARCH model. The model is expressed as;

$$\sigma_t^d = \omega + \sum_{i=1}^{p} \alpha_i (|\varepsilon_{t-i}| + \gamma_i \varepsilon_{t-i})^d + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^d \tag{2.58}$$

Where d is a positive exponent, and γ_i denotes the coefficient of leverage effect. It is important to note that when d equals to two, the model reduces to the basic GARCH model with leverage effect (Kozhan, 2009).

CHAPTER THREE

ANALYSIS OF LEVERAGE EFFECT IN CONTAINER FREIGHT INDICES BASED ON EGARCH MODEL

3.1. AIM OF THE STUDY

This study aims to investigate the existence and properties of leverage effect in container freight indices. CCFI and SCFI have been developed by SSE to reflect the overall fluctuation level of international container shipping market. Since their early stages these indices are considered as major economic indicators for international trade and shipping. Due to the impacting factors such as international politics, economics and supply-demand relationship; the violent fluctuation of CFI & SCFI makes it difficult for international trade and shipping stakeholders to make sound decisions. To this end, conducting researches on the volatility characteristics of container shipping market holds great importance to avoiding operational risks both in theory and practice.

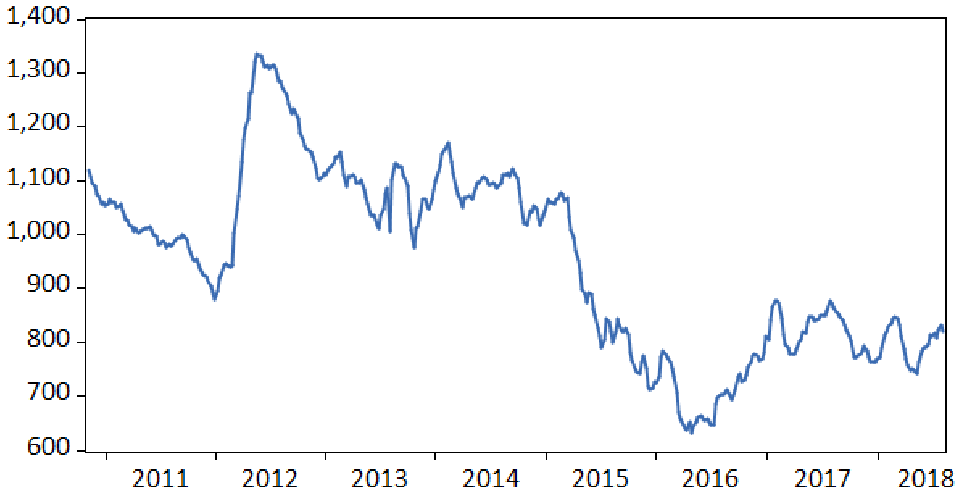
3.2. METHODOLOGY

This study employs a financial time series analysis as the main research methodology. After conducting a research upon the changing and asymmetric volatility models to decide on which time series approach to be taken, an EGARCH model was constructed in order to analyze the leverage effect in container freight indices.

3.2.1. Data

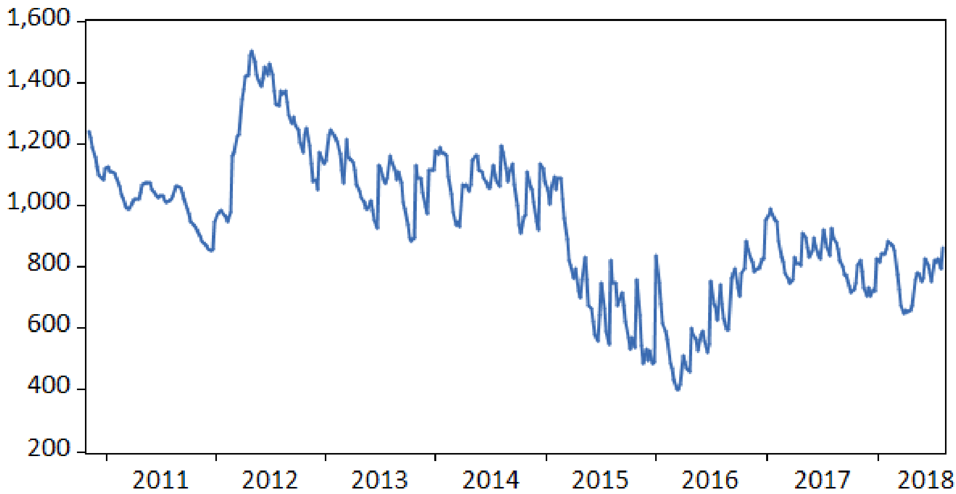
The study is conducted on weekly CCFI and SCFI data published by Shanghai Shipping Exchange between 11 May 2010 – 27 July 2018. Both indices consist of 392 observations, which is a considerable number to capturing the changes in asymmetric volatility over time and volatility clustering. All of the necessary data were gathered from Bloomberg to prevent the mismatch and missing value problems that may occur from gathering data from different databases which do not perfectly correspond with each other. Figure 8 and Figure 9 provides the time stream graph of CCFI and SCFI in order to provide an understanding of the trend in the container freight rates.

Figure 10: Time Trend of CCFI



Source: Processed by Author, Data from Bloomberg, 2018

Figure 11: Time Trend of SCFI



Source: Processed by Author, Data from Bloomberg, 2018

After examining the graphs of two indices we can make preliminary judgments that both of the indices possess volatility patterns that are very large and unstable.

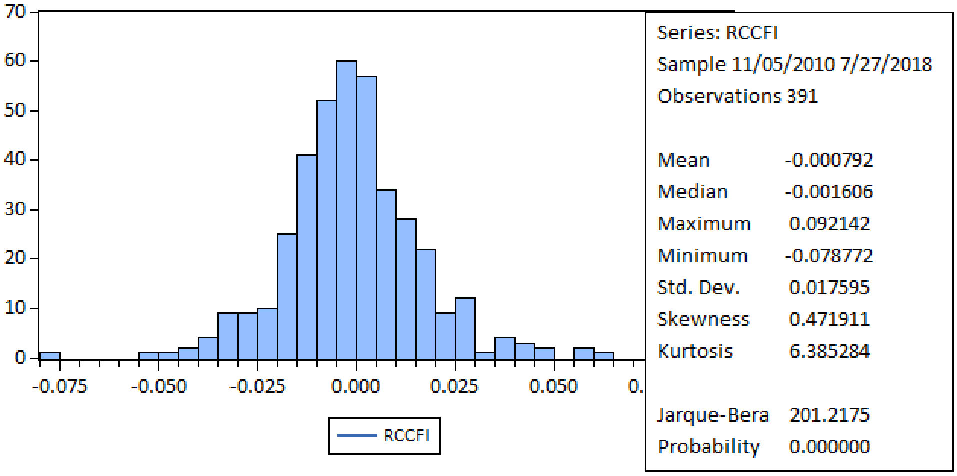
3.2.1.1. Preparation of the Data

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

$$R_t = log\left(\frac{P_t}{P_{t-1}}\right) \tag{3.1}$$

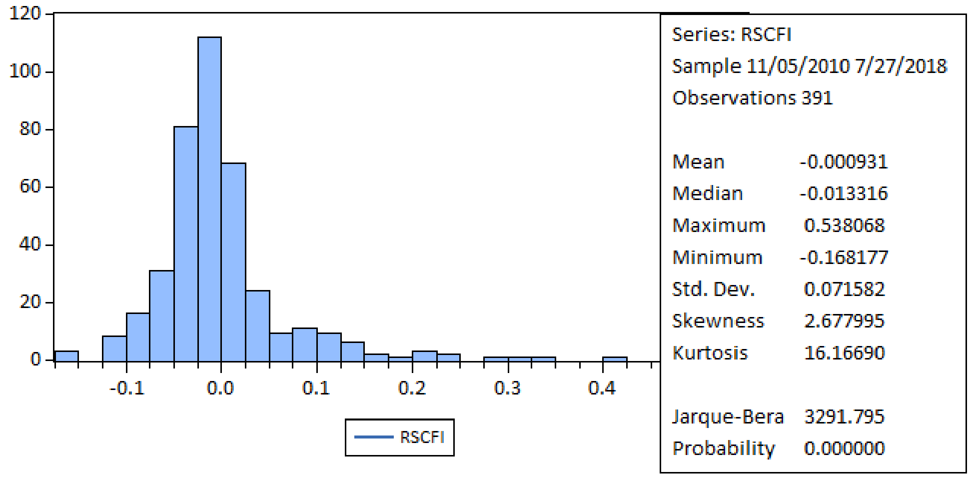
Which P_t is the freight index value and R_t is the freight index rate of return value. After the conversion both CCFI and SCFI return series descriptive statistics, histograms and trend graphs were given in order at the Figure 10 and Figure 11 below.

Figure 12: Histogram and Descriptive Statistics of RCCFI



Source: Processed by Author, Data from Bloomberg, 2018

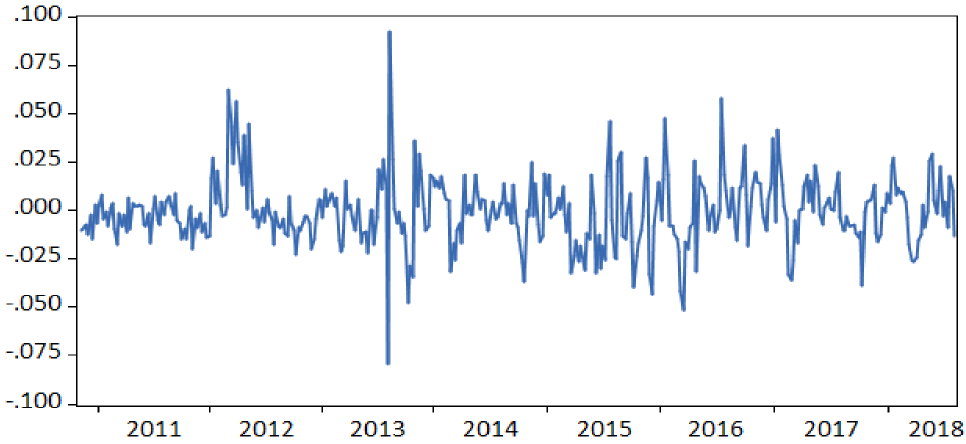
Figure 13: Histogram and Descriptive Statistics of RSCFI



Source: Processed by Author, Data from Bloomberg, 2018

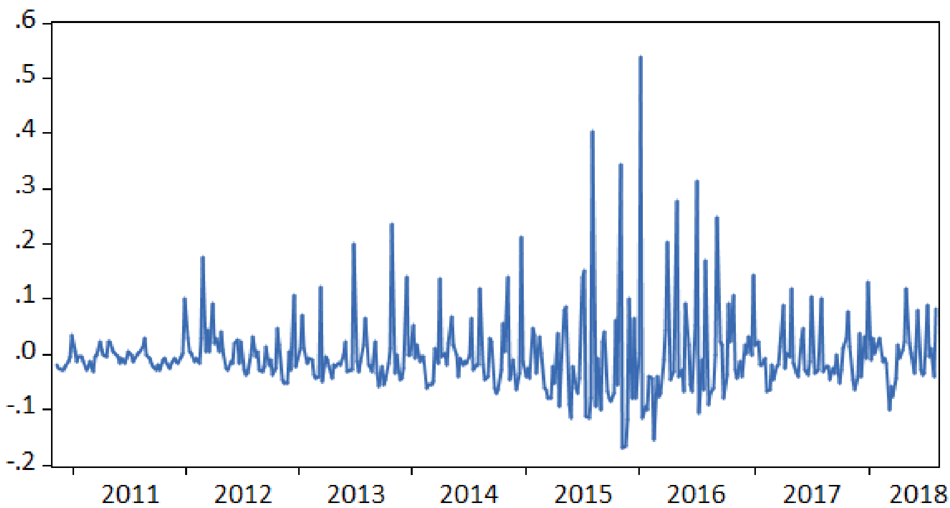
When Figures 10 and Figure 11 are examined it can be said that both of the series are skewed to the right. Also both of the series possess very high kurtosis values compared to the normal distribution kurtosis of 3, which proves the fat tails seen in financial time series are indeed present at the RCCFI and RSCFI series. Also the normal distribution assumption for both series are tested empirically with the Jarque-Bera normal distribution test (Jarque and Bera, 1987). According to the test results none of the series distributed normally. Lastly the descriptive statistics of both series strongly hint that they possess a heteroscedastic structure.

Figure 14: Return Values of CCFI



Source: Processed by Author, Data from Bloomberg, 2018

Figure 15: Return Values of SCFI



Source: Processed by Author, Data from Bloomberg, 2018

When both the CCFI and SCFI rate of return graphs at Figure 12 and Figure 13 were examined, we can make preliminary calls that both of the series are stationary and constantly waving by the zero mean. Also the volatility clustering is visually obvious for both of the series. Although time stream graphs give first glance information and some insights regarding the stationarity of the series, it is a must to conduct unit root tests and examine the correlogram to ensure the stationarity. For this matter both Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests were applied and the results of the unit root tests are given in the Table 2 and Table 3 below.

Table 2: ADF Unit Root Test Results

	RCCFI	RSCFI
ADF test value	-13.54139	-15.40970
1% critical value	-3.446906	-3.446992
5% critical value	-2.868732	-2.868771
10% critical value	-2.570668	-2.570688

Source: Processed by Author, Data from Bloomberg, 2018

In the ADF Unit Root Test, the obtained test value is compared to its model with a constant consisting of;

$$\Delta y_t = \mu + \phi y_{t-1} + \sum_{j=1}^{p} \psi_i \Delta y_{t-j} + \varepsilon_t \tag{3.2}$$

The lag length was selected as 2 for SCFI, and 0 for RCCFI based on the Schwarz Information Criterion (SIC). The null hypothesis of ADF test, which is H_0 represents the existence of unit root in the series which implies that $\phi = 1$. To test this hypothesis, the acquired test statistics are compared with the critical value levels of 1%, 5%, and 10%. If the test statistics value is lesser than a critical value level, the null hypothesis can be rejected for that percentage of significant level. Otherwise, we cannot reject the null hypothesis (Said and Dickey, 1984). According to the table the null hypothesis H_0 is rejected at all the significance levels and therefore it can be said that both of the series do not possess unit root and therefore they are stationary according to ADF. As for the PP test the results are;

Table 3: PP Unit Root Test Results

	RCCFI	RSCFI
PP test value	-13.84620	-20.89360
1% critical value	-3.446906	-3.446906
5% critical value	-2.868732	-2.868732
10% critical value	-2.570668	-2.570688

Source: Processed by Author, Data from Bloomberg, 2018

Although being similar to the ADF test, the Phillips-Perron test regression does not include lagged valued of the first differences. Instead the PP test fixes the t-statistic using a long run variance estimation by implementing a Newey-West covariance estimator proposed by Newey and West (1987). What makes the PP test favorable for financial time series is its ignoring of any serial correlation in the test regression with a constant;

$$\Delta y_t = \mu + \phi y_{t-1} + \varepsilon_t \qquad (3.3)$$

Where ε_t is stationary and may be heteroscedastic. The PP test corrects serial correlations and heteroscedasticity in the errors of ε_t. This is also another advantage of PP test over ADF is that it is robust to general forms of heteroscedasticity in the error term (Phillips and Perron, 1988). In addition to that there is no need to specify a lag length for the regression, because the bandwidth is automatically implemented in PP calculation by Newey-West covariance estimator. The null hypothesis of PP test, which is H_0 represents the existence of unit root in the series which implies that $\phi = 1$. The testing of the null hypothesis follows the same steps as the ADF. Therefore according to Table 3 the null hypothesis H_0 is rejected at all the significance levels and it can be said that both of the series do not possess unit root and therefore they are stationary according to PP unit root test.

After conducting the ADF and PP tests, the correlogram of both series need to be examined to determine the existence of serial correlation. A correlation simply means the visual representation of a series autocorrelation, partial autocorrelation and Q-statistics for the specified lag length. Figure 14 and Figure 15 below represent the correlogram of the indices under 36 lag length.

Figure 16: Correlogram of RCCFI

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.357	0.357	50.342	0.000
		2	0.194	0.075	65.141	0.000
		3	0.105	0.016	69.504	0.000
		4	0.092	0.044	72.851	0.000
		5	0.062	0.010	74.373	0.000
		6	-0.018	-0.064	74.498	0.000
		7	-0.065	-0.060	76.196	0.000
		8	-0.008	0.042	76.222	0.000
		9	0.020	0.029	76.375	0.000
		10	-0.051	-0.073	77.418	0.000
		11	-0.079	-0.046	79.957	0.000
		12	-0.014	0.048	80.034	0.000
		13	-0.025	-0.029	80.285	0.000
		14	-0.037	-0.029	80.847	0.000
		15	0.001	0.047	80.847	0.000
		16	-0.009	-0.009	80.882	0.000
		17	0.023	0.013	81.107	0.000
		18	-0.033	-0.058	81.563	0.000
		19	-0.102	-0.083	85.854	0.000
		20	0.009	0.088	85.891	0.000
		21	0.014	-0.000	85.977	0.000
		22	0.013	0.006	86.053	0.000
		23	-0.017	-0.014	86.172	0.000
		24	0.066	0.085	87.983	0.000
		25	0.134	0.090	95.553	0.000
		26	0.085	-0.018	98.615	0.000
		27	0.013	-0.036	98.688	0.000
		28	-0.007	-0.007	98.708	0.000
		29	0.005	-0.024	98.716	0.000
		30	-0.045	-0.073	99.580	0.000
		31	-0.095	-0.040	103.40	0.000
		32	-0.076	-0.001	105.89	0.000
		33	0.023	0.079	106.11	0.000
		34	-0.027	-0.055	106.42	0.000
		35	-0.018	0.018	106.55	0.000
		36	-0.047	-0.012	107.53	0.000

Source: Processed by Author, Data from Bloomberg, 2018

At the first glance the Autocorrelation (AC) and Partial Correlation (PAC) values of RCCFI decrease over time and only the few first values are outside of the critical levels. Therefore, it can be said that the series definitely possess serial correlation and does not have a MA parameter.

Figure 17: Correlogram of RSCFI

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.043	-0.043	0.7221	0.395
		2	-0.102	-0.104	4.8345	0.089
		3	-0.212	-0.224	22.689	0.000
		4	0.121	0.091	28.543	0.000
		5	0.110	0.081	33.349	0.000
		6	-0.145	-0.172	41.718	0.000
		7	-0.132	-0.093	48.662	0.000
		8	-0.045	-0.058	49.487	0.000
		9	0.170	0.068	61.161	0.000
		10	-0.097	-0.134	64.993	0.000
		11	-0.065	-0.043	66.720	0.000
		12	0.135	0.195	74.158	0.000
		13	0.009	-0.091	74.190	0.000
		14	-0.027	-0.078	74.493	0.000
		15	-0.111	0.006	79.572	0.000
		16	0.178	0.162	92.544	0.000
		17	0.022	-0.055	92.739	0.000
		18	-0.058	-0.078	94.117	0.000
		19	-0.109	0.053	98.992	0.000
		20	-0.064	-0.103	100.71	0.000
		21	0.184	0.032	114.78	0.000
		22	-0.078	-0.031	117.32	0.000
		23	-0.047	0.005	118.24	0.000
		24	-0.044	-0.009	119.05	0.000
		25	0.229	0.140	141.02	0.000
		26	0.023	0.033	141.25	0.000
		27	-0.044	0.015	142.08	0.000
		28	-0.025	0.018	142.34	0.000
		29	0.026	0.041	142.63	0.000
		30	-0.010	-0.104	142.67	0.000
		31	-0.156	-0.108	153.10	0.000
		32	-0.021	0.045	153.29	0.000
		33	0.014	-0.052	153.38	0.000
		34	0.159	0.099	164.32	0.000
		35	-0.114	-0.057	169.91	0.000
		36	-0.031	0.055	170.31	0.000

Source: Processed by Author, Data from Bloomberg, 2018

When we look at the AC and PAC values of RSCFI, unlike the RCCFI correlogram values of this one do not decrease over time and many of them are outside of the critical values at various lag periods. Therefore, it can be said that the series definitely possess serial correlation and have MA parameters. But to be certain both of the series will be tested to decide on what order of AR and MA parameters are required in the model.

3.2.2. Model Selection

In the model selection period both of the series were estimated under various combinations of AR and MA parameters with the OLS method. Therefore, alternative models for both RCCFI and RSCFI were created and their properties are given below at the Table 4 and Table 5.

Table 4: Alternative Models of RCCFI

Model	Log-Likelihood	AIC	SIC	HQ
(1,0)(0,0)	1052.112580	-5.366305	-5.335854	-5.354235
(1,1)(0,0)	1053.320974	-5.367371	-5.326770	-5.351278
(2,0)(0,0)	1053.214060	-5.366824	-5.326223	-5.350731
(0,2)(0,0)	1051.886630	-5.360034	-5.319433	-5.343941
(2,1)(0,0)	1053.358832	-5.362449	-5.311699	-5.342333
(1,2)(0,0)	1053.353327	-5.362421	-5.311670	-5.342305
(3,0)(0,0)	1053.262383	-5.361956	-5.311205	-5.341840
(0,1)(0,0)	1046.746174	-5.338855	-5.308405	-5.326786
(0,3)(0,0)	1052.374998	-5.357417	-5.306666	-5.337301
(3,3)(0,0)	1060.255245	-5.382380	-5.301179	-5.350194
(4,0)(0,0)	1053.647096	-5.358809	-5.297908	-5.334670
(4,2)(0,0)	1059.488711	-5.378459	-5.297258	-5.346273
(1,3)(0,0)	1053.396382	-5.357526	-5.296625	-5.333387
(3,1)(0,0)	1053.360168	-5.357341	-5.296440	-5.333202
(2,2)(0,0)	1053.359311	-5.357337	-5.296436	-5.333198
(0,4)(0,0)	1052.986303	-5.355429	-5.294528	-5.331290
(2,4)(0,0)	1057.272230	-5.367121	-5.285920	-5.334936
(3,4)(0,0)	1059.836462	-5.375123	-5.283771	-5.338914
(4,3)(0,0)	1059.788095	-5.374875	-5.283524	-5.338667
(1,4)(0,0)	1053.722008	-5.354077	-5.283026	-5.325915
(4,1)(0,0)	1053.651699	-5.353717	-5.282666	-5.325555
(2,3)(0,0)	1053.459466	-5.352734	-5.281683	-5.324572
(3,2)(0,0)	1053.418614	-5.352525	-5.281474	-5.324363
(4,4)(0,0)	1055.603141	-5.348354	-5.246852	-5.308122
(0,0)(0,0)	1025.401088	-5.234788	-5.214488	-5.226742

Source: Processed by Author, Data from Bloomberg, 2018

Table 5: Alternative Models of RSCFI

Model	Log-Likelihood	AIC	SIC	HQ
(3,2)(0,0)	504.963120	-2.547126	-2.476075	-2.518964
(2,3)(0,0)	504.817547	-2.546381	-2.475330	-2.518219
(3,3)(0,0)	505.024453	-2.542325	-2.461123	-2.510139
(4,2)(0,0)	505.008774	-2.542244	-2.461043	-2.510059
(2,4)(0,0)	504.961152	-2.542001	-2.460800	-2.509815
(4,3)(0,0)	506.763852	-2.546107	-2.454755	-2.509898
(3,4)(0,0)	505.065691	-2.537420	-2.446069	-2.501212
(2,2)(0,0)	495.631647	-2.504510	-2.443609	-2.480371
(4,4)(0,0)	506.969988	-2.542046	-2.440545	-2.501814
(0,3)(0,0)	490.295235	-2.482329	-2.431578	-2.462213
(3,0)(0,0)	489.288971	-2.477181	-2.426431	-2.457066
(4,0)(0,0)	490.898417	-2.480299	-2.419398	-2.456160
(0,4)(0,0)	490.744810	-2.479513	-2.418612	-2.455374
(1,3)(0,0)	490.603500	-2.478790	-2.417889	-2.454651
(3,1)(0,0)	490.088673	-2.476157	-2.415256	-2.452018
(0,0)(0,0)	476.728491	-2.428279	-2.407978	-2.420232
(1,1)(0,0)	482.694550	-2.448565	-2.407965	-2.432473
(4,1)(0,0)	491.148101	-2.476461	-2.405410	-2.448299
(1,4)(0,0)	490.776030	-2.474558	-2.403507	-2.446395
(2,1)(0,0)	483.722274	-2.448707	-2.397957	-2.428591
(1,2)(0,0)	483.592483	-2.448043	-2.397293	-2.427928
(0,1)(0,0)	477.194667	-2.425548	-2.395098	-2.413479
(1,0)(0,0)	477.087541	-2.425000	-2.394550	-2.412931
(0,2)(0,0)	480.018202	-2.434876	-2.394275	-2.418783
(2,0)(0,0)	479.212908	-2.430757	-2.390156	-2.414664

Source: Processed by Author, Data from Bloomberg, 2018

When choosing between the alternative models, the significance of the coefficients, magnitudes of SIC and Log-Likelihood values are taken into the consideration. Therefore, the model with the all coefficients significant, smallest SIC and largest Log-Likelihood values are determined as optimal models. For RCCFI series it is AR(1), and for RSCFI series it is ARMA(3,2) type least squares models with Maximum Likelihood (ML). The modeling of the series in these structures are given below at Table 6 and Table 7.

Table 6: Modeling RCCFI with AR(1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000822	0.001380	-0.595496	0.5519
AR(1)	0.357217	0.035389	10.09390	0.0000
SIGMASQ	0.000269	1.16E-05	23.23647	0.0000

R-squared	0.128013	Mean dependent var	-0.000792
Adjusted R-squared	0.123518	S.D. dependent var	0.017595
S.E. of regression	0.016472	Akaike info criterion	-5.366305
Sum squared resid	0.105276	Schwarz criterion	-5.335854
Log likelihood	1052.113	Hannan-Quinn criter.	-5.354235
F-statistic	28.48039	Durbin-Watson stat	2.049058
Prob(F-statistic)	0.000000		

Source: Processed by Author, Data from Bloomberg, 2018

Table 7: Modeling RSCFI with ARMA(3,2)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000925	0.004103	-0.225392	0.8218
AR(1)	-0.249214	0.055721	-4.472489	0.0000
AR(2)	-0.812601	0.049288	-16.48678	0.0000
AR(3)	-0.260049	0.048230	-5.391871	0.0000
MA(1)	0.205758	0.052034	3.954274	0.0001
MA(2)	0.804175	0.046161	17.42093	0.0000
SIGMASQ	0.004414	0.000194	22.78458	0.0000

R-squared	0.136345	Mean dependent var	-0.000931
Adjusted R-squared	0.122850	S.D. dependent var	0.071582
S.E. of regression	0.067041	Akaike info criterion	-2.547126
Sum squared resid	1.725884	Schwarz criterion	-2.476075
Log likelihood	504.9631	Hannan-Quinn criter.	-2.518964
F-statistic	10.10367	Durbin-Watson stat	2.001978
Prob(F-statistic)	0.000000		

Source: Processed by Author, Data from Bloomberg, 2018

After the simple models for RCCFI and RSCFI were constructed, both of the models will be tested against the heteroscedasticity with White and ARCH-Lagrange Multiplier (LM) tests and the results are given at the Table 8 and Table 9 below.

Table 8: White Heteroscedasticity Test Results for RCCFI AR(1) and RSCFI ARMA(3,2) Models

	RCCFI AR(1)	RSCFI ARMA(3,2)
F-Statistic	4.70E+25	1.05E+25
Prob.	0.0000	0.0000

Source: Processed by Author, Data from Bloomberg, 2018

The White test tests for heteroscedasticity of the model with the H_0 null hypothesis representing homoscedasticity. The test basically regresses the squared residuals of our model on our regressor and its squared regressor via an auxiliary regression (White, 1980). When looked at the test results it can be said that for both cases the H_0 is rejected and both models have heteroscedasticity. Since the White test is considered not very efficient way of giving final decision on heteroscedasticity in financial time series, an additional ARCH-LM test is also applied and its results are given below.

Table 9: ARCH-LM Test Results for RCCFI AR(1) and RSCFI ARMA(3,2) Models

		RCCFI AR(1)	RSCFI ARMA(3,2)
ARCH 1-2 Test	F-Statistic	36.73328	0.144217
	Prob.	0.0000	0.7043
ARCH 1-5 Test	F-Statistic	8.433955	1.189575
	Prob.	0.0000	0.3136
ARCH 1-10 Test	F-Statistic	4.297570	5.046597
	Prob.	0.0000	0.0000

Source: Processed by Author, Data from Bloomberg, 2018

ARCH-LM test checks for the existence of heteroscedasticity by regressing squared residuals of the model on lagged values of the squared residuals and a constant (Engle, 1982). With the H_0 null hypothesis representing homoscedasticity, both RCCFI and RSCFI models were tested on lags one, five and ten, which are the most commonly tested empirical lag lengths. When looked at the results, both of the models reject the homoscedasticity assumption of the test, although RSCFI model only after ten and more lag lengths, it can be safely said that both time series models possess strong autoregressive and heteroscedastic structures which are applicable for ARCH or GARCH type modelling.

3.2.3. Estimation

After getting strong evidences on the existence of ARCH effects in the models of return of container freight index series, and in the light of the studies main motivation on finding out the leverage effect and its properties on these indices an EGARCH(1,1,1) model is constructed with the existing mean equation parameters. The estimation is made on EViews 10 statistical analysis software with index return values of both CCFI and SCFI between 11.05.2010 and 27.07.2018 including 392 observations (391 after the log-return conversation).

As for the distribution of errors, unfortunately Gaussian normal distribution assumption is incapable for accounting all of the leptokurtosis that appears in financial time series such as freight index data. Due to the highly volatile nature of the market large numbers of extremely high and low return rates are observed. Which is a clear sigh of fatter tailed error distributions. The EGARCH models with student-t distribution however, assumes the conditional distribution of errors are t distributed. With its mean being zero, variance one, and degrees of freedom v the student-t conditional density function can be described as $v > 2$;

$$\rho\left(z_{jt}|\Omega_{t-1}\right) = \Gamma\left(\frac{v+1}{2}\right)\Gamma\left(\frac{v}{2}\right)^{-1}\left((v-2)\pi\right)^{-\frac{1}{2}}\left(1+z_{jt}^{2}(v-2)^{-1}\right)^{\frac{-(v+1)}{2}} \qquad (3.4)$$

The explanation of this choice is due to v is also being the leptokurtosis degree. When $1/v$ nears to zero, the student-t distribution also gets close to a Gaussian normal distribution. As our model is estimated with student-t error distribution, degrees of freedom becomes an extra parameter to be estimated with the other conditional variance equation parameters.

After the initial estimation of RSCFI with ARMA(3,2)-EGARCH(1,1) model, the AR(3) parameter which was determined on OLS estimator lost its significance at the GARCH modeling. After removing the insignificant AR operator from the model, the model had an increase in its log-likelihood value from 641.3428 to 644.4600, Durbin-Watson test statistics value from 2.240886 to 2.268010 and decrease in all of the information criterions which are Akaike Information Criterion (AIC), Hannan-Quinn Information Critarion (HQ), and SIC. Therefore, the new modification improved the model in all aspects as well as reducing the effects of information loss generated by application of AR and MA operators. The results of AR(1)-EGARCH(1,1) model for RCCFI and ARMA(2,2)-EGARCH(1,1) model are given at the Table 10 and Table 11 below.

Table 10: Estimation Results for RCCFI AR(1)-EGARCH(1,1) Model

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.002647	0.001076	-2.459312	0.0139
AR(1)	0.438373	0.039613	11.06649	0.0000
Variance Equation				
ω	-0.481630	0.232734	-2.069440	0.0385
α	0.164376	0.051333	3.202154	0.0014
γ	-0.094986	0.037163	-2.555904	0.0106
β	0.955558	0.026653	35.85167	0.0000
T-DIST. DOF	4.105871	0.837364	4.903329	0.0000

R-squared	0.117960	Mean dependent var	-0.000769
Adjusted R-squared	0.115687	S.D. dependent var	0.017611
S.E. of regression	0.016561	Akaike info criterion	-5.667907
Sum squared resid	0.106416	Schwarz criterion	-5.596720
Log likelihood	1112.242	Hannan-Quinn criter.	-5.639688
Durbin-Watson stat	2.208391		

Source: Processed by Author, Data from Bloomberg, 2018

Table 11: Estimation Results for RSCFI ARMA(2,2)-EGARCH(1,1) Model

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.009160	0.001635	-5.601231	0.0000
AR(1)	-0.313630	0.096555	-3.248218	0.0012
AR(2)	-0.737494	0.078120	-9.440481	0.0000
MA(1)	0.436392	0.091627	4.762717	0.0000
MA(2)	0.817063	0.069534	11.75054	0.0000
Variance Equation				
ω	-0.226139	0.073768	-3.065526	0.0022
α	0.249006	0.116175	2.143365	0.0321
γ	-0.174365	0.084650	-2.059827	0.0394
β	0.978211	0.009397	104.0975	0.0000
T-DIST. DOF	2.550220	0.381910	6.677536	0.0000

R-squared	0.041584	Mean dependent var	-0.000824
Adjusted R-squared	0.031601	S.D. dependent var	0.071750
S.E. of regression	0.070607	Akaike info criterion	-3.262005
Sum squared resid	1.914378	Schwarz criterion	-3.160114
Log likelihood	644.4600	Hannan-Quinn criter.	-3.221611
Durbin-Watson stat	2.268010		

Source: Processed by Author, Data from Bloomberg, 2018

Since the equation of EGARCH model being;

$$ln(\sigma_t^2) = \omega + \beta\, ln(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \qquad (3.5)$$

The parameter ω is variance intercept of the model. Where parameter β is the measurement of volatility persistence which also known as the GARCH effect. If the β value is large, longer periods of time is required for volatility to disperse and effects of a shock to be removed. The large number also implies greater fluctuations. For both RCCFI and RSCFI the parameter is even above 0.90 range, which is expected at most financial time series. The high value of lag coefficient means that returns of both container freight indices require very long times to get rid of the effects of external shocks and fluctuate wildly during innovation periods. The results suggest that shocks in return of CCFI and SCFI indices only disperse 4.5% and 2.2% each week.

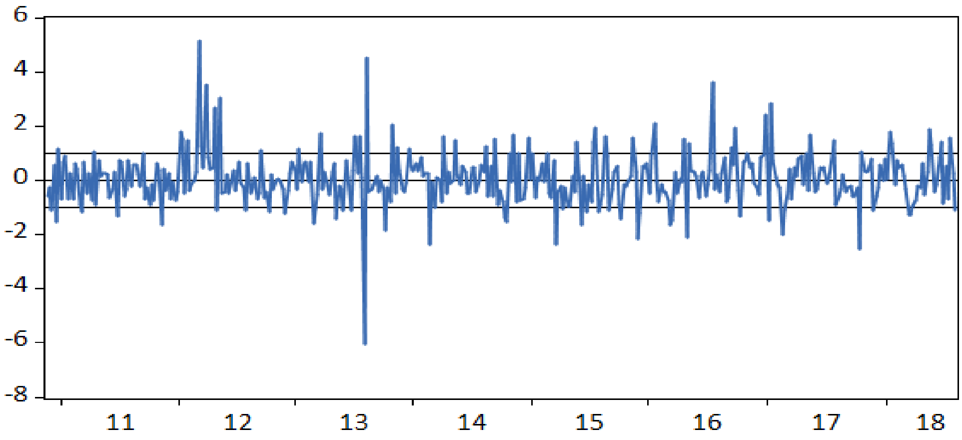
The parameter α is the return coefficient of the model, which is also known as the ARCH effect. The larger the α value becomes, the quicker it shows the movements in the markets and fluctuate longer. When the estimation results are examined it can be said that RSCFI reflects the movements of container freight market quicker and more sensitively than the RCCFI. Also both of their α values are larger than 0.1, which means volatility of both indices are very sensitive to happenings of the container market. The significance of this parameter proves the existence of volatility clustering in both indices.

And finally the parameter γ is the magnitude of models asymmetric volatility, which also known as the leverage effect parameter. When γ results in zero, it means that the volatility is symmetric for the series. If the parameter results in positive or negative value and becomes significant then it means the leverage effect is undeniable for the series. The sign of the γ value determines the properties of leverage effect. If γ results in a negative value, that means negative shocks or bad news generates more volatility than positive shocks or good news. If γ results in a positive value it can be said that positive shocks destabilize the series more than the negative shocks. According to the results from Table both RCCFI and RSCFI possess leverage effect with a negative γ value, latter having slightly more effect than the first one due to its proven sensitivity in this research. Which means bad news generate more volatility for both of the container indices than the good ones. One possible reason for that because container shipping and also shipping in general is such a capital intensive industry. When a negative development occurs in the market stakeholders might react more harshly than they react in the positive developments. Because when considering the properties of the market a negative investment and even a false investment can lead to bankruptcy, while reacting to positive happenings of the market is usually a win more decision.

3.2.4. Post Estimation Diagnostics

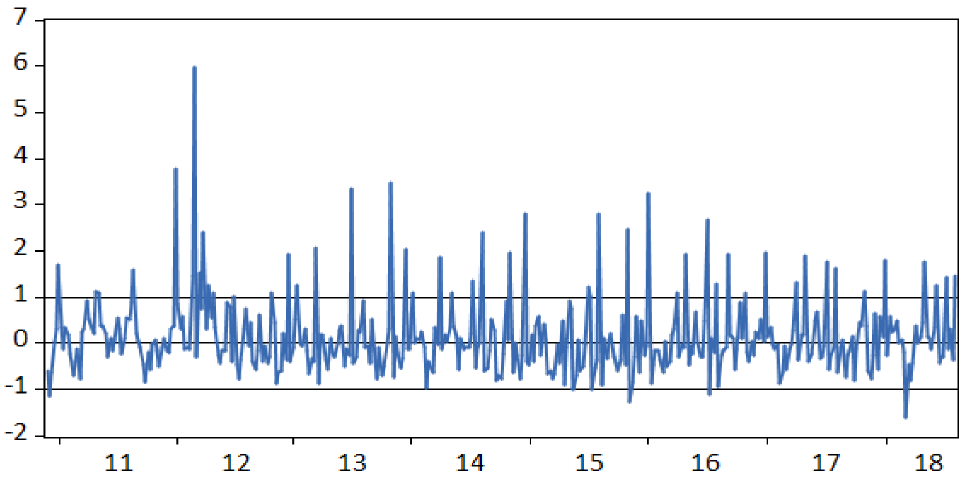
To prove the further validity of the constructed models, numerous residual diagnostics had to be made. Residuals of a correctly specified model has to be similar to a white noise process. Firstly, the line graphs of standardized residuals given in Figure 16 and Figure 17 for both models to be examined.

Figure 18: Standardized Residuals of RCCFI AR(1)-EGARCH(1,1) Model



Source: Processed by Author, Data from Bloomberg, 2018

Figure 19: Standardized Residuals of RSCFI ARMA(2,2)-EGARCH(1,1) Model



Source: Processed by Author, Data from Bloomberg, 2018

When both graphs are examined, it can be said that both of the standardized residual series show a typical visual representation of a white noise process. Both of the residual series appear to be out of trend and constantly swing by the zero mean. For giving the final decision on the model was specified right, correlograms of both the models residuals have to be examined to prove the absence of serial correlation. Correlograms of both models are given below at the Figure 18 and Figure 19.

Figure 20: Correlogram of RCCFI AR(1)-EGARCH(1,1) Model

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.074	-0.074	2.1256	
		2	0.067	0.062	3.8989	0.048
		3	0.033	0.043	4.3402	0.114
		4	0.034	0.036	4.8049	0.187
		5	0.036	0.036	5.3148	0.256
		6	0.019	0.018	5.4522	0.363
		7	-0.060	-0.066	6.9089	0.329
		8	0.024	0.009	7.1427	0.414
		9	0.057	0.064	8.4340	0.392
		10	-0.006	0.003	8.4508	0.489
		11	-0.111	-0.120	13.401	0.202
		12	0.053	0.036	14.531	0.205
		13	-0.031	-0.012	14.923	0.246
		14	-0.033	-0.045	15.371	0.285
		15	0.048	0.053	16.297	0.296
		16	-0.046	-0.019	17.169	0.309
		17	0.049	0.039	18.171	0.314
		18	-0.030	-0.040	18.548	0.355
		19	-0.130	-0.132	25.470	0.113
		20	0.012	0.006	25.525	0.144

*Probabilities may not be valid for this equation specification.

Source: Processed by Author, Data from Bloomberg, 2018

Figure 21: Correlogram of RSCFI ARMA(2,2)-EGARCH(1,1) Model

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.003	0.003	0.0029	
		2	0.025	0.025	0.2539	
		3	-0.074	-0.074	2.4298	
		4	0.095	0.095	5.9679	
		5	0.016	0.018	6.0649	0.014
		6	-0.041	-0.052	6.7275	0.035
		7	-0.027	-0.013	7.0274	0.071
		8	0.024	0.021	7.2515	0.123
		9	0.088	0.079	10.322	0.067
		10	-0.053	-0.052	11.467	0.075
		11	-0.068	-0.065	13.319	0.065
		12	0.085	0.100	16.206	0.040
		13	0.011	-0.013	16.257	0.062
		14	0.036	0.029	16.788	0.079
		15	-0.038	-0.004	17.378	0.097
		16	0.053	0.037	18.524	0.101
		17	0.018	0.011	18.649	0.134
		18	-0.012	-0.028	18.707	0.176
		19	-0.059	-0.035	20.151	0.166
		20	-0.098	-0.097	24.131	0.087

*Probabilities may not be valid for this equation specification.

Source: Processed by Author, Data from Bloomberg, 2018

When the correlograms are inspected both AC and PC values appear to be within the confidence intervals for both of the index models. Which means the standardized residuals of the model do not have serial correlation and they are indeed white noise processes. Which brings us to the conclusion of saying that the both models were specified correctly.

CONCLUSION

Shipping in general is known as a business with wild freight fluctuations. Because of its close relations and interactions with the commodity markets, the global maritime transportation market possesses various business cycles. Due to being a derived demand, maritime transportation industry is one of the few markets in which the happenings in the global economy felt most and quickest. To help investors and other decision makers with that matter various global authorities created indices to serve as a medium and reflector of the market. After the introduction of standard shipping containers much has changed both in maritime and logistics industries. These standardized shipping units quickly become a core part of the logistics and thus connecting markets together. Therefore, it is important to study the effects of the shocks on the shipping, especially in container shipping which is the fastest growing branch of the marine transportation. To understand the nature of the volatility at the container freight market and invest according to it, one must search for and employ proper tools in the analysis of changing volatility studies, just like most financial time series.

In the context of econometrics, it is expected from time series applications to have autocorrelation problem, and from cross-section applications to have heteroscedasticity problem. That being said, financial time series mostly suffer from both heteroscedasticity and autocorrelation issues. To overcome this obstacle, ARCH type models which centers themselves around the heteroscedasticity concept were developed. Since the proposition of first model of this type, many extensions and variations were developed for more detailed research.

In this study the leverage effect itself and its properties on container shipping markets were examined via modeling the weekly return values of CCFI and SCFI with EGARCH methodology. Study aimed to prove the existence of the leverage effect phenomenon in container shipping and analyze how different shocks effect the volatility of the market.

At the first part of the study nature and development of container freight indices were explained in detail. It is worth noting that over time the gathering of container freight data and production of container indices slowly started to shift from small liner company panel groups to larger panels, from that to even larger panels with more shipping actors, and finally from that to e-business oriented anonymous data with weekly number of tens of millions. Due to being the most established and the most used one, the indices produced by SSE were selected as the main series to be used in the study.

In the second part of the study the risk and return structure of shipping and univariate models of changing volatility and asymmetric volatility were examined. Also the factors making shipping an exotic investment compared to other asset investment types are laid out with the differences of CAP and RAP models. In an econometric point of view both conditional and unconditional variance estimators, their developments and usages were explained in detail. Also how the mentioned models explain the volatilities of financial return series is discussed with their similarities and differences. Therefore, EGARCH type models validity of analyzing the leverage effect was justified.

In the last part of the study weekly return values of container freight indices, namely CCFI and SCFI between 11 May 2010 – 27 July 2018, both consisting of 392 observations. The examined return values show leptokurtosis and volatility clustering, both being fore signs of heteroscedasticity. For the next stage autoregressive structures of both series were determined by estimating with an OLS estimator. After determining the AR and MA operators for series residuals of the series were tested against heteroscedasticity via White and ARCH-LM tests. According to the heteroscedasticity test results residuals of the index return series which were estimated with OLS, are under considerable ARCH effect. Therefore, with the aim of the study in mind return of the CCFI found to be most suitable for AR(1)-EGARCH(1,1) model with Student-t error distribution and return of the SCFI found to fit best to ARMA(2,2)-EGARCH(1,1) with Student-t error distribution model after various modifications. After the estimation, standardized residuals of both models were examined for serial correlation. It was proven that both of the models standardized residuals were free of any remaining serial correlation effects and followed a white noise pattern.

The estimation results indicated that both volatility persistence and leverage effect are obvious for both freight index returns. According to the estimations the container freight market has negative leverage, in other words bad news generate more volatility for both of the container indices than the good ones. In addition to this, it can be said that container freight market requires a long time for the effects of the shocks to be disappear on their own. The volatility generated for return of CCFI and SCFI by those shocks persist through approximately 22 weeks and 45 weeks in order. Also both indices have very high sensitivity ratios, which means that both indices will reflect quickly to the happenings of the shipping and economy in general. This also proves the phenomenon of shipping industry being one of the quickest and harshest reflecting sectors to the developments in the global economy. All of these being said it is also important to note that the aim of SSE to create both indices to mirror the movements of the market seems to be fulfilled.

All being said with the RAP type structure of the container shipping market considered, the leverage effect emerged as a core function of the freight mechanism of the market. The results were in line with the theory of maritime economics. With the high sensitivity, high shock persistence and negative leverage effect properties considered, container shipping industry which is already infamous with its knifes edge position on the stability, will surely has to stay on alert for any crisis situation at the global economy and will be tested harshly as it has been throughout the recent history.

REFERENCES

Baltic Exchange (2018). Baltic Indices and Methodology. https://www.balticexchange.com/market-information/methodology.shtml, (15.07.2018)

Black, F. (1976). Studies of Stock Price Volatility Changes. *Proceedings of the Business and Economics Section of the American Statistical Association*, 177-181.

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroscedasticity. *Journal of Econometrics*, 31, 301-327.

Brooks, C. (2014). *Introductory Econometrics for Finance, Third Edition.* New York: Cambridge University Press.

Campbell, J. A., Lo, A. W., and MacKinlay, A. C. (1998). *The Econometrics of Financial Markets*. New Jersey: Princeton University Press.

Ding, Z., Granger, C. W. J. and Engle, R. F. (1993). A Long Memory Property of Stock Market Returns and a New Model. *Journal of Empirical Finance*, 1, 83-106.

Drewry (2018). World Container Index Methodology and Information. http://www.worldcontainerindex.com/index.php?mode=staticContent&id=methodology, (28.07.2018)

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, 50, 987-1007.

Engle, R. F. and Bollerslev, T. (1986). Modeling the Persistence of Conditional Variances. *Econometric Reviews*, 5, 1–50.

Engle, R. F., Lilien, D. M. and Robins, R. P. (1987). Estimating Time Varying Risk Premia in the Term Structure: The ARCH-M Model. *Econometrica*, 55, 391–407.

Fama, E. F. and Miller M. H. (1972). *The Theory of Finance*. Illinois: Dryden Press.

Freightos (2018). Freightos Baltic Global Container Index Methodology and Information.
https://www.freightos.com/international-freight-index, (28.07.2018).

Hayashi, F. (2000). *Econometrics*. New Jersey: Princeton University Press.

Jarque, C. M. and Bera, A. K. (1987). A Test for Normality of Observations and Regression Residuals, *International Statistical Review*, 55(2), 163-172.

Kavussanos, M. G. and Visvikis, I. D. (2016). *The International Handbook of Shipping Finance.* London: Macmillan.

Kozhan, R. (2009). *Financial Econometrics with EViews*. Frederiksberg: Ventus Publishing.

Mandelbrot, B. B. (1963). The Variation of Certain Speculative Prices. *The Journal of Business*, 36, 394-419.

Nelson, D. B. (1991). Conditional Heteroscedasticity in Asset Returns: A New Approach. *Econometrica*, 59, 347-370.

Newey, W. K. and West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, 55(3), 703-708.

Phillips, P. C. B. and Perron, P. (1988). Testing for Unit Roots in Time Series Regression, *Biometrika*, 75, 335-346.

Said, S. E. and Dickey, D. (1984). Testing for Unit Roots in Autoregressive Moving-Average Models with Unknown Order. *Biometrika*, 71, 599-607.

Schwert, W. (1989). Stock Volatility and Crash of ’87. *Review of Financial Studies*. 3, 77–102.

Shanghai Shipping Exchange (2018). Shanghai Shipping Exchange and Index Information.
http://en.sse.net.cn/index.jsp (28.07.2018)

Taylor, S. (1986). *Modeling Financial Time Series*. New York: John Wiley & Sons.

Tsay, R. S. (1986). *Analysis of Financial Time Series*. New York: John Wiley & Sons.

White, H. (1980). A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. Econometrica, 48(4), 817-838.

Yifei, Z., Dali, Z. and Yanagita, T. (2018). Container Liner Freight Index Based on Data from E-booking Platforms. *Maritime Policy & Management*, DOI: 10.1080/03088839.2018.1443224

Zakoian, J. M. (1994). Threshold Heteroskedastic Models. *Journal of Economic Dynamics and Control*. 18, 931-944.