DOKUZ EYLÜL UNIVERSITY

GRADUATE SCHOOL OF SOCIAL SCIENCES

DEPARTMENT OF BUSINESS ADMINISTRATION

ACCOUNTING AND FINANCE PROGRAM

MASTER'S THESIS

VOLATILITY TRANSMISSION BETWEEN BALTIC DRY INDEX AND OIL PRICES AS A RISK INDICATOR

Meriç KARPAT

Supervisor

Assc. Prof. Dr. Habil GÖKMEN

İZMİR-2019

YÜKSEK LİSANS
TEZ ONAY SAYFASI

Üniversite	: Dokuz Eylül Üniversitesi
Enstitü	: Sosyal Bilimler Enstitüsü
Adı ve Soyadı	: Meriç KARPAT
Öğrenci No	: 2014800574
Tez Başlığı	: Volatility Transmission Between Baltic Dry Index and Oil Prices As a Risk Indicator
Savunma Tarihi	: 22/08/2019
Danışmanı	: Assist Prof.Dr. Habil GÖKMEN

JÜRİ ÜYELERİ

Ünvanı, Adı, Soyadı	**Üniversitesi**	**İmza**
Assist Prof.Dr. Habil GÖKMEN	DOKUZ EYLUL UNIVERSITY	....
Assist Prof.Dr. Efe Çağlar ÇAĞLI	DOKUZ EYLUL UNIVERSITY	....
Prof.Dr.Cevdet A.KAYALI	IZMIR OF ECONOMIC UNIVERSTY	....

Meriç KARPAT tarafından hazırlanmış ve sunulmuş olan bu tez savunmada başarılı bulunarak oy birliği(X) / oy çokluğu( ) ile kabul edilmiştir.

Doç. Dr. Erkan GÖKSU
Müdür V.

DECLARATION

I hereby declare that this master's thesis titled "Volatility transmission between Baltic Dry Index and Oil Prices as a risk indicator" 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.

Date

… / 07 / 2019

Meriç KARPAT

Signature

ABSTRACT

Master's Thesis

Volatility Transmission Between Baltic Dry Index and Oil Prices

As a Risk Indicator

Meriç KARPAT

Dokuz Eylül University

Graduate School of Social Sciences

Department of Business Administration

Accounting and Finance Program

This thesis aims to examine the correlation between the Baltic Dry Index which is published by Baltic Exchange in London on a daily basis and in terms of global trade is considered as one of the most important indicators by many and Crude Oil Prices for which the Brent Crude Oil Prices to be taken as a reference variable.

The research expects to put forth the spillover effect that the Brent Crude Oil price fluctuations have upon Baltic Dry Index through the cost of shipping directly affecting the vitality of international trade and production. In this context, the study firstly conducts a thorough review of available literature in order to establish the conclusion that by means of MV DCC-GARCH volatility approach, there is volatility transmission from Brent Crude Oil prices to the BDI. Afterward, respective variables were explained and volatility models were discussed. And ultimately, the test results for the selected model were explained and interpreted.

Empirical findings indicate that as the cost of energy for ocean transportation accounts for a significant amount of total costs, concordantly fluctuations of oil prices for several reasons directly affect the performance of the Index on a global scale.

Keywords: Baltic Dry Index, Crude Oil, Volatility, ARCH, DCC-GARCH, Spillover

ÖZET

Yüksek Lisans Tezi

Bir Risk Göstergesi Olarak Baltic Dry Index ile Petrol Fiyatları Arasındaki Oynaklık Geçişkenliği

Meriç KARPAT

Dokuz Eylül Üniversitesi

Sosyal Bilimler Enstitüsü

İngilizce İşletme Anabilim Dalı

Muhasebe ve Finansman Programı

Bu tez, Londra'da Baltık Borsası tarafından günlük olarak yayınlanan ve pek çok kişi tarafından küresel ticaretin en önemli göstergelerinden biri olduğu düşünülen Baltık Kuru Yük Endeksi ile Ham Petrol fiyatları arasındaki korelasyonu incelemeyi amaçlamaktadır. Ham Petrol için Brent Ham Petrol fiyatları referans olarak alınmıştır.

Bu araştırma, Brent Ham Petrol fiyatlarındaki dalgalanmaların, uluslararası ticaret ve üretimin canlılığını doğrudan etkileyen taşıma maliyetleri aracılığıyla Baltık Kuru Yük Endeksi üzerindeki yayılma etkisini ortaya koymayı beklemektedir. Bu bağlamda, çalışma DCC-GARCH oynaklık yaklaşımı aracılığıyla Brent Ham Petrol fiyatlarından Baltık Kuru Yük Endeksine oynaklık geçişkenliği olduğu sonucuna varabilmek için ilk olarak mevcut literatürün kapsamlı bir incelemesini gerçekleştirmiştir. Ardından sırasıyla ilgili değişkenler açıklanmış ve oynaklık modelleri üzerinde durulmuştur. Ve nihai olarak da seçilen metoda ilişkin test sonuçları açıklanıp yorumlanmıştır.

Ampirik bulgular, enerji maliyetleri okyanus taşımacılığındaki toplam maliyetlerin önemli bir kısmını oluşturduğu için bu duruma paralel olarak bir çok sebepten dolayı Endeksin performansını küresel ölçekte etkilemekte olduğunu göstermiştir.

Anahtar Kelimeler: Baltık Kuru Yük Endeksi, Ham Petrol, Oynaklık, ARCH, DCC-GARCH, Yayılma

TABLE OF CONTENTS

VOLATILITY TRANSMISSION BETWEEN BALTIC DRY INDEX AND CRUDE OIL PRICES AS A RISK INDICATOR

CHAPTER 2

METHODOLOGY

CHAPTER 3

DATA CHARACTERISTICS

CHAPTER 4

VOLATILITY TRANSMISSION

ABBREVIATIONS

ADF : Augmented Dickey-Fuller

AR : Autoregressive

ARCH : Autoregressive Conditional Heteroskedasticity

ARCH-M : Autoregressive Conditional Heteroskedasticity in Mean

ARIMA : Autoregressive Integrated Moving Average

ARCH-LM : Autoregressive Conditional Heteroskedasticity Lagrange Multiplier

BCI : Baltic Capesize Index

BDI : Baltic Dry Index

BEKK-GARCH : Baba, Engle, Kraft, Kroner Generalized Autoregressive Conditional Heteroskedasticity

BFI : Baltic Freight Index

BHSI : Baltic Handysize Index

BPI : Baltic Panamax Index

BSI : Baltic Supramax Index

CCC-GARCH : Constant Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity

CEV : Constant Elasticity of Variance

DCC-GARCH : Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity

EIA : Energy Information Administration

EMD	: Empirical Mode Decomposition
E&P	: Exploration and Production
FFA	: Forward Freight Agreements
FNN	: False Nearest Neighbors
GARCH	: Generalized Autoregressive Conditional Heteroskedasticity
GDP	: Gross Domestic Product
GJR-GARCH	: Glosten, Jagannathan and Runkle Generalized Autoregressive Conditional Heteroskedasticity
LDC	: Less Developed Countries
LPG	: Liquefied Petroleum Gas
MGARCH	: Multivariate Generalized Autoregressive Conditional Heteroskedasticity
NGL	: Natural Gas Liquids
OLS	: Ordinary Least Squares
OPEC	: Organization of the Petroleum Exporting Countries
TCAVG	: Time Charter Average
UNCTAD	: United Nations Conference on Trade and Developement
VARX	: Vector Error Correction Model
VC-GARCH	: Varying Correlation Generalized Autoregressive Conditional Heteroskedasticity
VEC-GARCH	:Vec Generalized Autoregressive Conditional Hteroskedasticity
VECM	: Vector Error Correction Model
VLCC	: Very Large Crude Carriers
WTI	: West Texas Intermediate

LIST OF TABLES

LIST OF FIGURES

APPENDICES

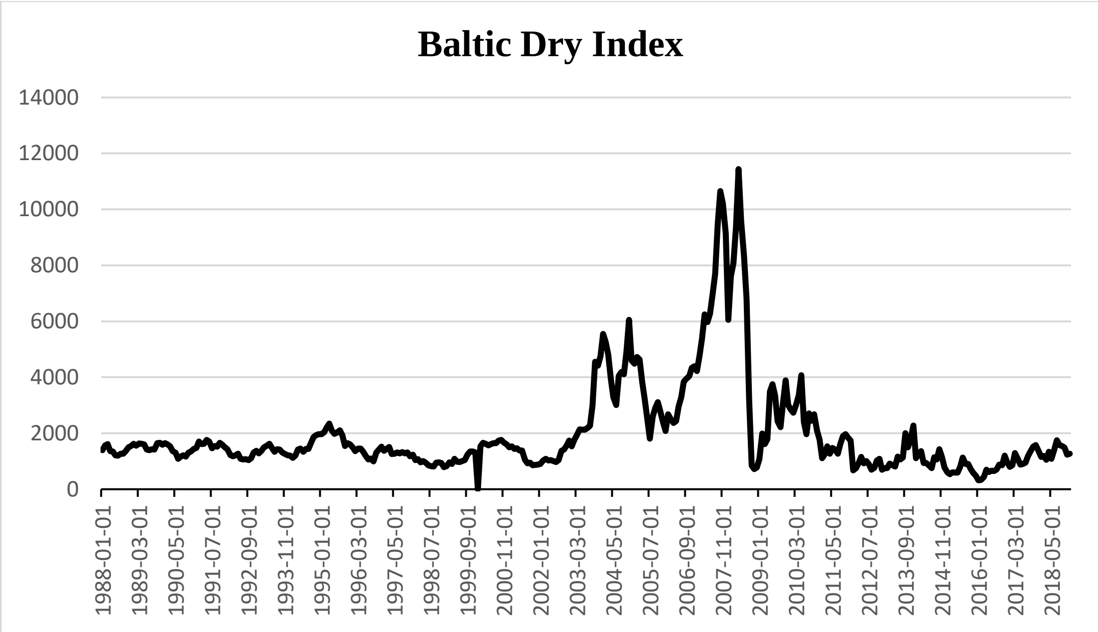
INTRODUCTION

Since its first formation, the BDI has been one of the most attractive and handy indicators in terms of the shipping costs and a crucial gauge on the volume of global trade and production levels (Lin and Sim, 2013: 1-18). Investors all the time search for easy interpretable economic indicators that they could utilize to assist them take comprehensive investing decisions. Accordingly, for quite a while, Baltic Dry Index has been considered as an economic indicator on a global scale. Additionally, it is a well-known fact that the BDI relies heavily on crude oil prices and port docking fees and this status indirectly makes BDI sensitive to global overall demand and industrial outputs to meet the requirements.

Technically, any change in the industrial activities will cause parallel alterations in other important indicators such as employment rates, capacity usage ratios and liquidity levels in an economy as a whole. Hence, the economy would experience alterations in cash availability which leading to positive cashflows or investments in the money or capital markets due to quantitative expansion to raise return of money market product price fluctuations. On top of that, oil prices have been considered as a crucial subject in the sense of symbolizing the effect of supply shocks in augmenting cyclical alterations. According to Kilian and Park (2009); the revulsion of the U.S. real stock returns to oil price shocks varies considerably and as per the authors this variation is mainly because of the hidden shocks which can not be seen at the first sight behind oil price variations.

The graph depicted below emphasizes how the BDI showed a rather volatile outlook especially between 2004 and 2009, the period it acted like a bubble. A fundamental factor of this increase was associated with commodity prices, especially oil. The index afterward quickly dropped back at a record pace to historical means and has kept its weak outlook despite there has been observed a recovery in international trade. One of the reasons for that was during the “bubble years”, exceedingly constructed vessels have participated in the market, procuring capacity growth over demand increase. Recently, the BDI maintains its low levels, accentuating a condition of excess capacity in the shipping industry compared to current global production level. Peculiarly, the nature of the shipping industry is proportionally foreseeable with any deviations in the cost of shipping costs mostly because of the alteration in global demand to raw inputs (Stopford, 2009). Principally, the Baltic Dry Index monitorize the cost of transportation for commodities, such as coal, steel, cement, and grain around the world, and this is why the said indicator can be utilized as a universal economic measurement since it projects the direction of end-user prices of products utilizing dry bulk centered raw materials.

Figure 1: Baltic Dry Index (Monthly, 1988-2018)



Source: Koyfin, 2019

The BDI is principally necessary since the Less Developed Countries (LDC) exports depend largely on the trade of primary goods of which the generality stands upon bulk vessels for international shipment. From this point of view, the BDI pictures the crucial elements of the cost of trade, constituting an adverse impact on the LDCs' efficiency in international trade. Realizing the significant connection between the cost of transporting raw materials and the production of industrially demanded materials has directed many researchers to put numerous studies on the subject concludes that the demand for goods and, hence, economic activity, is depictured by the course that the BDI follows. In another saying, the BDI and stock markets relationship emerges in a roundabout way, meaning the BDI reflects changes in economic activity, and that situation consequently influences the course of the international capital markets and trade. The connection between economic liveliness and financial markets has so far been on a large scale emphasized both in the applied and theoretical literature. An alteration in the Baltic Dry Index has the ability to present investors' thoughts regarding the worldwide supply and demand expectations. Researchers reviewing the subject think that an up or downtrend in the index will be an important sign of future economic volatility. It's predicated through demand for raw materials will provide important signs as to the faith or the directions of the markets. Mentioned basic inputs are purchased to build or maintain construction and infrastructure. It is considered that when the BDI escalates, the rise symbolizes more robust demand to merchandises, since the plants use more inputs more to give countenance to the expansion in production whilst an adverse move in the BDI represents the producers encounter inadequate demand to consumable products, leading to companies consequently a possible production cut. Actually, in addition to its macro capabilities, the BDI could also exhibit some speculative gestures, as there are also future contracts moving with the BDI which are being traded on over the counter markets. In this context the underlying freight market might as well witness some speculative attempts by parties making transactions on the market. As understood, regardless of our standpoint, BDI with in relation to many other elements is one of the important indicators giving signs regarding the current international economic conjuncture.

1.1 Empirical Studies on the Field

Specifically, the augmentation of the researches on volatility transmission and cointegration aftermath of the economic downturn that unfolded in late 2008 has laid the groundwork for different applications' rise through multi-disciplines. Similar to many other sectors, the shipping market as well has experienced recession following the outburst of the U.S rooted financial collateralized debt obligation crisis which had a destructive and indigestible effect over the by nature interconnected economies and, in turn, put the world economy into recession. With the influence of this dramatic turmoil, in particular the volatility of the international shipping market too has captured close interest, and numerous studies focusing on the volatility has been executed. Over the last decade, different types of quantitative methods, (i.e Vector Auto-Regressive, GARCH types, and Vector Error Correction) have been extensively utilized in reviewing shipping market dynamics and estimation on various aspects. In this context, Due to the fact that the BDI carry the identity to reflect the freight rates and time charter levels in the dry bulk shipping segment and is generally perceived as an important indicator of economic activity, on the studies in the subject. Cullinane (1992) employs a Box-Jenkins approach using BFI (Baltic Freight Index) daily series to deduce a model that yields accurate predictions over the short term. An autoregressive model in the name of AR (3) is concluded as the best-fitted model with a short forecasting horizon being optimal. The objective of such a study was specified as forming a beneficial model to develop speculative strategies in the market. Lundgren (1996) suggested that dry bulk transportation cost changes were associated with the price changes of OPEC countries. Kavussanos (1996) utilized ARCH model for emphasizing the price volatility of VLCCs and explored that the prices of various ships have different reactions to exogenous shocks. Veenstra and Franses (1997) detected that there are co-integration relations between multiple time series composed of freight tariffs. Cullinane et al. (1999) make comparisons among models to estimate the BFI and research the effect of the variation in the formation of the BFI that occurred in 1993 and concluded that the ARIMA model has the highest density and best prediction results. Additionally, Veenstra and Charalambides (2001) use the Vector Auto Regressive model to predict the trade flux of fundamental commodities used as compulsory in the production processes. Alizadeh and Nomikos (2003) use Forward Freight Agreements (FFAs) to predict the heading of freight rates requested on major routes in the future and concluded that they can not be benefited as estimators in that context and also that the forecasting veracity was invertedly in relation to maturity. Kavussanos et al. (2004) considered that Forward Freight Agreements operated as equalizers of the volatility in the rates of shipping course due to they are a part of the dry bulk market and they investigated the relationship between FFAs and spot return with GJR-GARCH model and use co-integration analysis and VECM modeling to investigate how strong FFAs can predict the Panamax market. Duru, Bulut, and Yoshida (2010) developed a long term fuzzy model and perform it to the annual time series of freight rates. Chung and Ha (2010) researched the long-run relation of BDI, euro-dollar interest rate, US stock prices, and China's iron imports employing the Pesaran's co-integration method. Duru and Yoshida (2011) submitted a new calculation model to establish long term freight index of dry cargo shipping utilizing the differential method in their equation and researched the lag and price elasticity of the bulk shipping market via the long-term freight index. The conclusions show that the log-linear model is not a convenient model for bulk shipping market estimation due to the spurious regression prospects. Alizadeh and Talley (2011) research the factors of dry bulk shipping freight rates and concluded that vessel tonnage, age, and voyage routes are requisite for freight quotations of dry bulk transportation. Bakshi, Panayotov, Skoulakis (2011) examined the proof for forecasting capacity of global stock market returns, commodity index returns, and growth in global real economic activity, based on the three-month growth rate of the Baltic Dry Index as base indicator and demonstrated that the growth rate of the BDI can forecast some of the stock markets in their study.The results disclosed in the study helped show the connection of the BDI as a predictor. Chen and Hsu (2012) focused on the movements of oil prices and proved that high volatility constitutes an obstacle to international commerce. Geman and Smith (2012) conducted financial analysis on BDI to present its key features and its relationship with the world economy. BDI behavior is found to be strongly different from behaviors of stocks, bonds and most commodities with a mean-reverting form of the Constant Elasticity of Variance (CEV) model. Duru, Bulut, and Yoshida (2013) also concluded on a later study that despite the fact that the Delphi forecasting is a practical instrument in decision processes and its high dependence on human imagination is possible to result in illogical decisions. Curtis and Thalassinos (2013) select non-linear analysis and implemented the False Nearest Neighbors (FNN) model in estimating the leading Baltic indices. It turns out to be that this model forecasts the BDI with superior precision compared to Baltic Exchange indices. Nonetheless, this model is rather vulnerable to noise, as the superiority could be damaged by the high frequency structure of times series. Zeng and Qu (2013) studied the BDI benefiting Empirical Mode Decomposition (EMD), resulting the said method externalize the non-linearity characteristics of the data and requested deeper researches to authenticate its feasibility. Ruan, Wang, Lu, and Qin (2015) examined the cross-correlation characteristics of crude oil expenses and BDI and concluded that the cross-correlations between BDI and crude oil expenses are considerably multifractal. Shen and Chou (2015) studied to find out if there are any causal relationships among the West Texas Intermediate oil prices and some selected Baltic Exchange indices and concluded that there is statistically significant co-integration among WTI and the Baltic indices. Uyar et al. (2016) suggested that dry cargo freight rate estimation method which has better accuracy than previous ones includes a generic algorithm based upon the recurrent fuzzy neural network. Tsioumas and Papadimitriou (2016) detected significant causality between the bulk cargo type vessel freight quotations and some of the commodity prices. Since most of the previous studies on the BDI are not interested in a GARCH model concentrating on the impact of DCC on the covariance matrix over time, "Tsouknidis (2016) focuses the presence of dynamic volatility transmission among the dry-bulk and tanker freight markets employing the multivariate DCC-GARCH model and the volatility spillover index improved by Diebold and Yilmaz (2012, 2009) and he revealed the presence of obvious volatility spillover effects in shipping freight markets which are more intense over the course of 2008 financial crisis." Tsioumas et al. (2017) aim to improve the estimation integrity of the Baltic Dry Index (BDI). In order to do that they built up a multivariate VAR model including external variables (VARX). The conclusions show that VARX model outputs better results than the ARIMA model, claiming that the chosen independent variables may considerably enhance the trueness of the BDI estimations. In a very recent study using panel regression and individual time-series regressions, Han, Wan, and Xu (2019) explored that the BDI has long-run predictability for exchange rates and exchange rate returns are adversely correlated to the changes in the BDI in the long run.

1.2 Baltic Dry Index

Today's Baltic Exchange was found just before the formation of the Chicago Board of Trade and the London Metal Exchange in the middle of 18th century (Geman and Smith, 2012: 98-109). Originally, the roots of Baltic Exchange can be encountered as early as 1744 in a coffee house known as Virginia and Baltic from which it obtained its name. This coffee house was a restaurant frequently visited by the British people to bargain the condition of contracts which includes the terms for transportation the commodities by cargo vessels (Baltic Exchange, 2019).

The BDI is an index daily disclosed by London centered Baltic Exchange and it is one of the most noteworthy indicators of the international trade marketplace of brokering shipping. The Baltic Dry Index is a leading indicator to its users since they calculate their firm quotas according to this index particularly for dry cargoes in bulk. With more than 600 entities and 3000 individuals being a part of the index- given the subscription-based calculation- the BDI today still stands as the sole independent maritime-focused information resource utilized by participants of international seaborne trade (Geman and Smith, pp.98-109). Since the “price” represents the demand to the vessels in circulation, the index thus is seen as a circuitous demand to the consumable goods by the end-users keeping also in mind that the inelastic structure of vessel supply in the short term leads to volatile movements against mentioned demand. Important mines like coal and steel or the resources including oil and various agricultural goods for still today serve as indispensable inputs for the intermediate or finished goods. This situation gives BDI the capability to represent the trend of industrial production and consuming on the world scale (Mowry and Pescatori, 2008: 8-12).

1.2.1 Composition of Baltic Dry Index

Originally, the model form of the Baltic Freight Index which today is known as Baltic Dry Index was started using in 1985. And firstly, trade contracts focused on shipping market were settled in the world’s first freight Futures Exchange. Despite the indication experienced several amendments through the years, the method used has basically maintained its unamended form ever since its release. The index banks on the collective bargaining of independent shipbrokers all over the globe. The brokers engaged in the market provide their technical reasoning regarding the overall rates adopting the free-market economy mindset. The numbers generated by the equation used in the BDI picture the current situation in the freight market (Baltic Exchange, 2019).

The heavily used routes ranging from the Pacific region to Atlantic and along with the fixtures among oceans are rather reflective of the world’s dominant dry bulk commerce. sustaining an equilibrium among various routes. The routes included in the calculation of the index have consistent and important rate of concluded contracts, whereas some trades experiencing cyclical closures such as Gulf of Aden are excluded. In order to maintain the indicative feature of the index, giant charterers with minority are carefully abstained, hence, the voyage routes which the contracts are extensively fixed on standard terms are favored.

The Baltic indices are considerably applied in the calculations and credible by many participants in the trade chain such as vessel owners, charterers and derivative market quantitative traders to configure their positions. These indices are not merely interpreted to resolve millions of dollars valued Forward Freight Agreement, but also and time charters and index-based charter parties. The index format of the BDI went into action as of 01.11.1999. Following 2006, Baltic Dry Index started being weighted as average of the BCI, BPI, and BSI of which the coefficient was 0.99800799. After the introduction a new index named BHSI, the updated calculation took a form to include this time mentioned 4 indices with a coefficient of 1.19262. For this reason, the BDI has an inclusionary approach as a rate indication for each of the rings on the commercial chain. After July 2009, BDI has taken a composite appearance of Time Charter Averages. Calculating the mean of below mentioned three sub-indices, Baltic Dry Index is weighted as stated below as of 01 March 2018.

The BDI calculation is based on the below equation;

[(Capesize5TCavg x 0.4) + (PanamaxTCavg x 0.3) +(SupramaxTCavg x 0.3)] x 0.10

Source: Baltic Exchange (2019) TCavg = Time charter average

In the formula stated above, Capesize5TCavg represents for particularly selected 5 capsize routes, PanamaxTCavg includes 4 routes in the BDI calculation and finally, SupramaxTCavg contains 10 sub-routes with each different weight after the latest revision made by Baltic Exchange. Details of each sub-routes for different sub-indexes in the production of BDI is depicted as follows;

Figure 2: Voyage Routes of BDI Sub-Indexes

Route Number	Route Description
Capesize 5 TC Index (Weight: 0.4)	
C8/14	"180.000mt Gibraltar/Hamburg Transatlantic Round Voyage"
C9/14	"180.000mt Continent/Mediterranean trip China-Japan"
C10/14	"180.000mt China-Japan transpacific Round Voyage"
C14	"180.000mt China-Brazil Round Voyage"
C16	"180.000mt Revised backhaul"
Panamax Index (Weight: 0.3)	
P1A/03	"74.000mt Skaw-Gibraltar, Transatlantic Round Voyage"
P2A/03	"74.000mt Skaw-Gibraltar trip to Taiwan-Japan"
P3A/03	"74.000mt Japan-South Korea transpacific Round Voyage"
P4/03	"74.000mt Japan-South Korea trip to Skaw-Passero"
Supramax Index (Weight: 0.3)	
S1B/58	"Canakkale trip via Mediterranean or Blacksea to China-South Korea"
S1C/58	"USG trip to China-South Japan"
S2/58	"North China one Australian or Pacific Round Voyage"
S3/58	"North China trip to West Africa"
S4A/58	"USG trip to Skaw-Passero"
S4B/58	"Skaw-Passero trip to USG"
S5/58	"West Africa trip via ECSA to North China"
S8/58	"South China trip via Indonesia to ECI"
S9/58	"West Africa trip via ECSA to Skaw-Passero"
S10/58	"South China trip via Indonesia to South China"

Source: Baltic Exchange, 2019

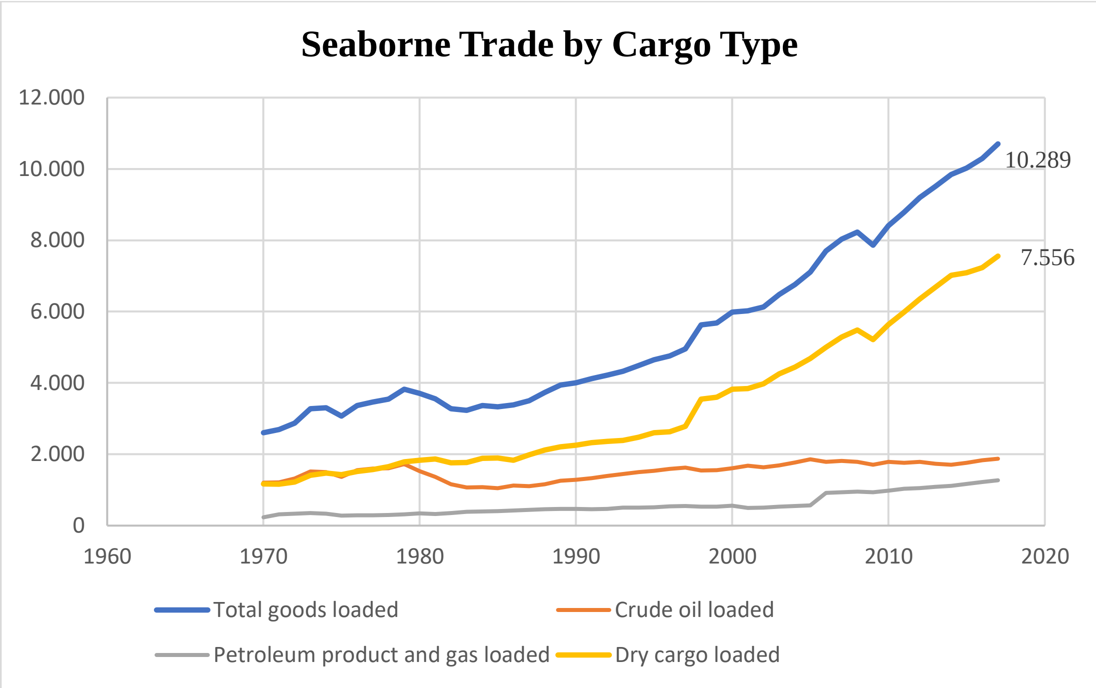
The above-plotted routes reflect the transportation costs of the commodities in the determined structures. The subject routes in the formation of BDI are calculated also based on their length as well as the geographic location. The reason for doing so is to assure that the specimen of transportation costs and their sub-indices become as representative as possible of the international sea trade cost. The route parts are evaluated according to their significance in dry bulk segment and briefed to reach daily disclosed BDI sub-index indications (Geman and Smith, pp.98-109)

1.2.2 Determinants of Baltic Dry Index

The BDI is largely impacted by various extrinsic factors. As far as clarified so far, there are several elementary causers revealing BDI changes as a whole. The demand for goods used in production or for the ultimate users is one of the main drivers of a possible alteration in the index. Any change for example in the quantity of produced agricultural goods will be represented by a parallel change in the index which consequently influencing the faith of the market. Another factor affecting the performance without a doubt is bunker prices which pose majority of the total cost in the sector. Cyclicality emerges as another element resulting in a parallel fluctuation in the index.

When we look at the graph pictured hereunder it becomes an obvious inference that over the course of the ’80s and ’90s international maritime sector gained acceleration with the expansion of the produced goods. This increase emerges by an annual basis change of roughly 2,5% in the positive direction. Additionally, the accrued rise over the years after the ’90s until the first decade of millennium is seen as approximately 30%. Concordantly, it is understood that the impact happens in a roundabout way by from the movements of GDP if we also review the production levels in the stated period. In a deeper review, it is obvious that the quickest surge by 4% has been realized over the recent 6 years in 2017. In the same year, 10.7 billion tons of different types of commodity were transported via long rage ocean vessels. This figure also shows that there is a relative change of 1,5 billion tons compared to the cargo level of 2012. According to UNCTAD data, the mentioned rise of 1,5 million has been greatly led by bulk cargo with the rest of about 300 million was liquid cargo types such as petroleum derivatives and gas. Asia has been undoubtedly biggest trading region. It would be clarified by the cargo amount of 4.4 billion supplied for sea transportation just in the Asia region. Conversely, the total cargo discharged in Asian ports realized as 6,5 billion, pointing out a deficit of 2,1 billion. The other areas recorded roughly 50% less comparing to these numbers. The number of commodities unloaded to the Oceania ports accrued as 180-190 million tons, relatively lower.

Figure 3: World Seaborne Trade by Types of Cargo (1970-2017)

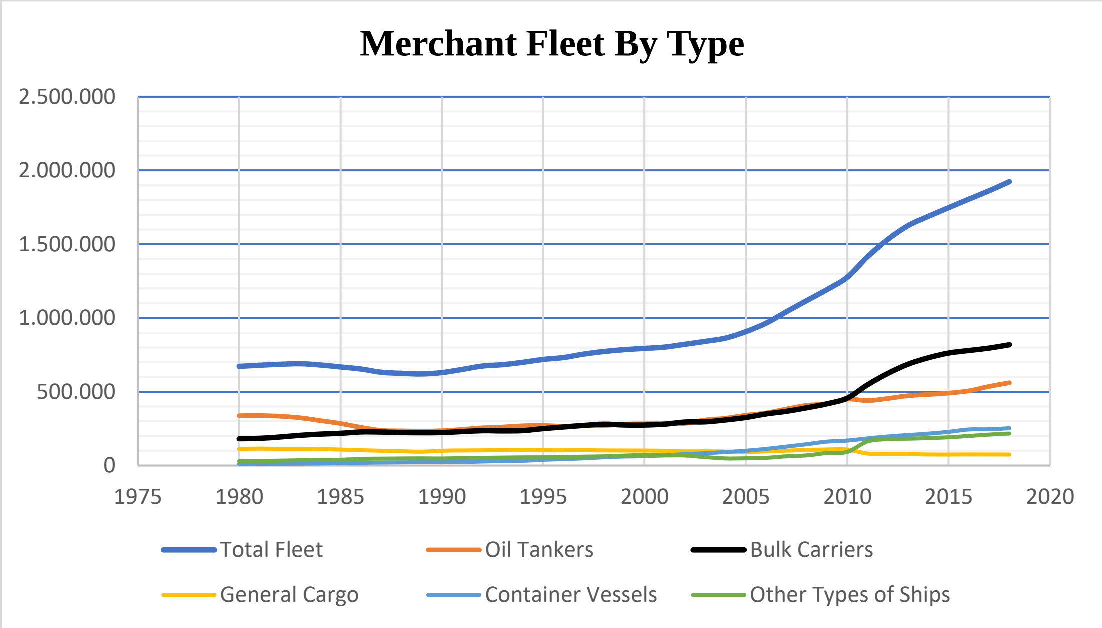


Source: UNCTAD, 2019 Volume: Metric Tons in Millions

Additionally, the equilibrium of ship supply and demand behaves like indicatory tool in calculating the bulk charter rates. Bulk cargo vessel charter rates also change according to the type of agreement and to the size of the ship. In general, there has been observed a more aggressive, volatile movements in the market of big vessels. This track of the respective index has also shown a more steady outlook in the small size vessels. As seen from line graph hereunder, the bulk carriers which is no surprise lead the total fleet by 818,613.000 deadweight tons in the world.

On the fleet type side also emphasized in the graph, the world fleet figured out a carrying capacity of 1,9 billion deadweight tons in January 2018. This figure comes out as above the year preceding it by 62 million deadweight tons. Latterly, the tonnage has dramatically risen on almost all the sections apart from general cargo vessels. Almost 50% of the world fleet has been constituted by the countries which pay relatively more importance to the vessel ownership and sea trade. Greece which is one them has maintained its lead supplementing 20 million deadweight tons in 2018 taking the slice of almost 17% of the total market. Other examples of such a tremendous share could be Japan, China, Germany respectively. It is also worth noting that despite not being owners, Marshall Islands, Panama and Liberia are the leaders in terms of the vessel registration of the world. In the light of this information it is no surprise and again worth noting that the vessel number in the seas is one of the major factors that drive the BDI.

Figure 4: World Merchant Vessel Fleet by Type (1980-2018)



Source: UNCTAD,2019 Volume: Deadweight tons in thousands

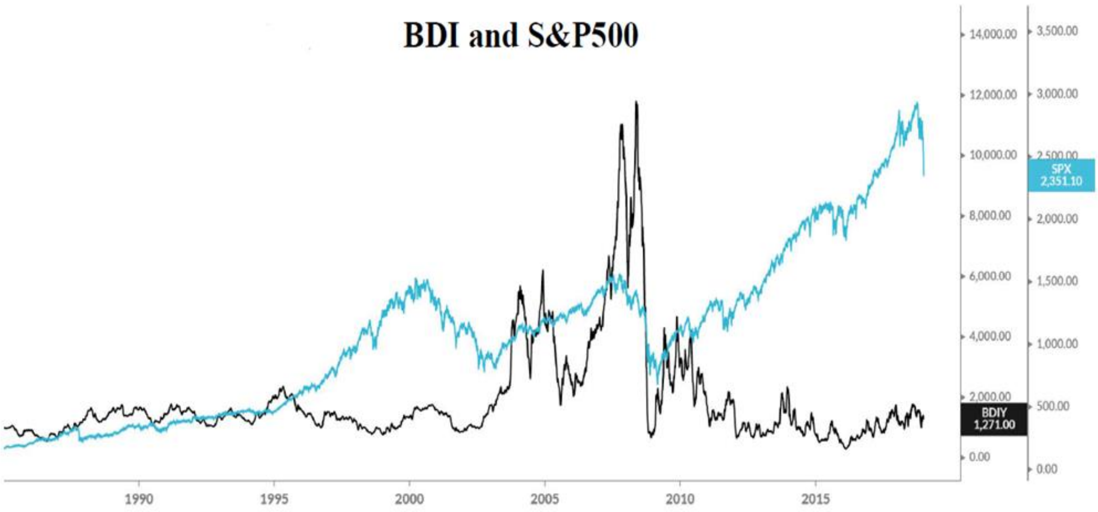
On the other hand, bunker costs equal to roughly 50-70% of total transportation costs incurred by the owners according to the vessel size and the rendered service type as to the discharging terms. Ocean transporters have to meet the mentioned costs to sustain their existence in the market over the long run. This would also mean that the charge of shipping costs to maintain its upward trend caused by the pressures of bunker prices. When we look out of this window and review the literature over the subject, we will understand that fuel charges demanded by the physical suppliers are in close connection with the bunker prices which show a fairly volatile outlook. Additionally, the likely shocks to oil prices will linearly impact the companies as a natural result of this situation as noted on (Notteboom and Vernimmen, 2008: 325-337). Bunker prices continually fluctuate because of the forces taking important decision in the market and the extent of oil extraction rate. The Intermediary Fuel Oil market is exceedingly sensitive to price changes. Due to this fact, companies always ponder over the decisions about where and where to bunker in order to protect their competitiveness on the market. Of course, there are various elements affecting the bunker decisions ranging from the geographical location of bunkering to the availability of the bunker type as these two matters simply affect the success of the taken decision in terms of different stances on the tax policies of countries. The subject that bunker prices affect the freight prices has paved the way for the emergence of a term called Bunker Adjustment factor. Accordingly, freights are quoted particularly as per this factorization method. This equation was invented following the world oil crisis. And it aims to protect voyage operator's revenue through transmitting the effect of alterations in the bunker prices from the vessel owners to the charterers (Notebooom and Cariou, 2009: 24-26).

Additionally, Goulielmos and Psifia (2006) emphasized the existence of freight prices having cyclical tendency of 2.25 – 4.5 years. As also stated in a study by (Tvedt, 2003: 221-230) that there is an event that freight prices are returning to their average levels, adding credence to the above-defined argument. He thought that if the freight rates deviate from the historical averages, they will reach back to the mean at later stages, pointing out cyclicality with the condition that the period needed for reversion feature is not changing. Particularly for freight prices, this was proved to hold true by the discovery of Goulielmos and Psifia (2006).

1.2.3 BDI as an Indicator of International Economic Activity

Despite technological developments, maritime transportation is still the most economic and prepotent way to carry the commodities from one place to another. It is so important that almost 90% of the goods produced are carried by the seaway. Roughly 75% of total carriage is dry cargo and approximately 70% of dry loads are dry bulk cargoes. The majority of these cargoes, coal and iron ore, are located with a share of 60% and if we add grain cargoes too, this rate rises to 70%. Approximately 60% of coal and iron ore cargoes go to East Asian countries and hence East Asian countries play a dominant role in dry bulk cargo trade. Among the Asia region, China, Japan, and India are at the forefront, while in the Pacific region Australia, India, Indonesia are important bulk cargo exporters. China has become the most important iron ore importer in the region after entering the World Trade Organization and has been a net coal importer since 2009, and as of 2018 China's coal importation has put itself in the first place in the world with Japan's follow. The mentioned raw materials are the most important raw materials of the real sector and industry, hence pose a crucial role in the world economy and industrial production. These raw materials are still the key elements in the production of steel and are the sine qua non of the production of final industrial products and semi-finished goods, such as automobiles, white goods, construction materials. Additionally, grain production and consumption constitute the major part of the economic prosperity of the countries due to the nature of the product and the improvement in the global economy. Transportation charges are on the other hand based on the supply and demand of vessels in the market. Since the demand and supply for ship tonnage in the short term are also inelastic, the slightest upward trend in ship transport demand in the short term also increases the transportation charges against the ship supply which is fixed to a certain extent, which leads to the rise of the BDI. Major economic measures such as income and wages, unemployment rate, consumer price index and in addition oil prices might be cheated or impacted by governments to misguide the people. But, Baltic Dry Index is very challenging to manipulate due mostly to it is affected by obvious movements of supply and demand (Bildirici et al, 2015: 416-424). The goods transporters enter the market according to their needs and demand for transportation. If the orders for the final consumption goods have increased or if there is an expectation that they will increase, then their raw materials are purchased, they enter the market as the demand for transportation and their impact is clearly seen in the BDI. The demand for transportation increases as raw materials are demanded, and transportation charges are increased according to the ship's supply and demand and this very close relationship with the supply and demand both on the vessel side and the good side makes BDI an active and signer indicator. The rise in the BDI is also a good measure of the increase in the capital stock markets, the rise in commodity prices, hence the rise in the global economy, the need for credit for the financing of the excess goods and transportation, and the increase in interest rates at the same time. Declines in the BDI indicate the opposite of all mentioned above of course. Therefore, it is suggested that there is a correlation between capital market indices and the BDI. However, this does not have to be one-to-one, that is, while the BDI is rising, the capital market index does not have to rise at the same time or vice versa. BDI increases from 1 to 3 months before the capital market index, afterward the capital market index gives a reaction to this rise in the BDI or similar action delay is observed in indices like BDI. This is due to the fact that the BDI value is based on the current ship supply with the ship's tonnage demanded on that day and the capital market indices reveal the increase or downfall of the share price of the companies according to the periodical balance sheet and profit and loss accounts. According to Simons (2011), there is very little connection between the BDI and the shares of the sea shipping companies or their profitability. When we investigated whether there is a correlation among the returns of various maritime companies and the BDI for a 3-month period, the result reveals that there is very little relationship. Because BDI is an index showing transportation charges, it is not related to the profitability of companies. The profitability of maritime transport companies depends on cost elements such as labor, fuel, and insurance. Moreover, the actors or investors in the capital market are looking ahead, not today. For example, the questions pointing out the levels of the new ship orders or how much tonnage will come into the market in the coming years are gaining importance by many market participants. In short, they do not act according to the current situation of BDI. This is obviously shown in the figure below.

Figure 5: BDI and SPX (Daily, 1985-2018)



Source: Koyfin, 2019

And it is important that we shouldn’t be unfair to the BDI. Although the BDI has increased significantly, it is still at 1250. These levels are still not very important for an index which saw 12,000s in 2008 and 4,600s in 2009 and 2010. On the other hand, as Simons (2011) has pointed out, what really matters for investors is to determine the stock values of what will happen in the future in the bulk dry cargo market. In spite of the views of Simons; Bakshi, Panayotov, and Skoulakis (2010) jointly stated that with a simple analysis in many markets, the predisposing slope coefficient of the increase rate of BDI in terms of the returns as profit share in the capital markets is extremely positive correlated and statistically significant. In addition, an increase in the BDI also in terms of commodity returns has shown a positive correlation and statistically satisfying results. There is also a positive correlation between BDI and industrial production. This situation is true for both advanced and emerging economies. BDI is a good pre-news stimulant for both the real sector and financial markets. As it can be understood from all these researches, even though there are some negative statements in recent years, when the BDI is taken into account with other variables and the factors affecting the BDI, it is still a good indicator and messenger when necessary corrections are made.

1.3 Oil Prices

Natively, the Brent Crude is generated from the Brent oil field. Brent term as a name stems from the acrostics of the genesis tiers of the oil areas. These fields include Broom, Ramnoch, Ness, and Tarbert. Brent type crude oil is accumulated in the North Sea region. The term also encompasses “Brent Blend, Forties Blend, Oseberg and Ekofisk crudes”. Brent crude has an American Petroleum Institute of roughly 38,06 equaling to a specific gravity of 0.835. There is also Sulphur in the Brent crude in the rate of 0.37%. In this regard, ratio of API gravity categorizes the petroleum type as light and heavy oil. Judging by the specifications stated above, we can infer that Brent oil is a sweet crude oil. On the contrary, it is worth noting that heavy oil is way less desirable as there are more processes that need to be incurred in the refining procedure. There is also another oil type in the name of West Texas Intermediate. However, we should also state that this sort of oil extracted in the United States is sweeter than Brent crude oil. Due to the fact that Brent oil price is primarily used as a benchmark in the trade oil, the petroleum output from different areas of the world basically is prone to be evaluated in line with this kind of oil. Acidity is another subject that needs to be considered in terms of the quality of the oil. The acidity of a petroleum resource is related to the degree of Sulphur in the oil. If the proportion of Sulphur is less, the oil gains the characteristics of becoming sweet, otherwise the oil becomes acetous because of the Sulphur ratio included. Sweet crude is more preferable because it provides easiness in satisfying the environmental prerequisites. As also stated previously, it would be easier to expose sweet crude to refining procedures (Noreng, 2002: 1036-1038).

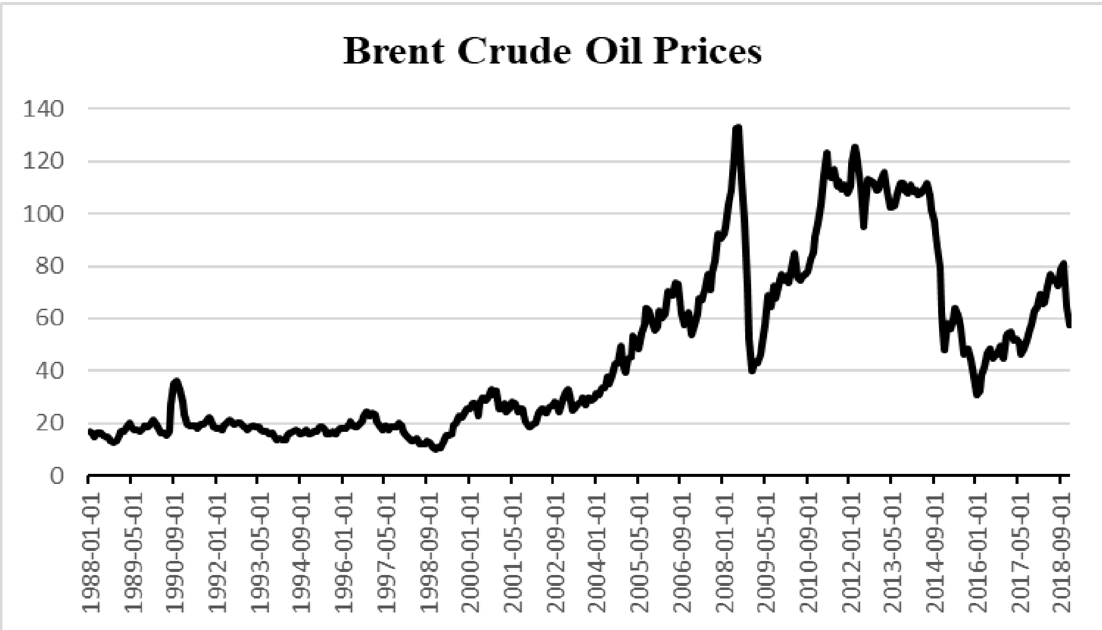
Brent crude is convenient for the fabrication of middle distillates. Northwest Europe is the main refining area in this regard. Additionally, Intercontinental Exchange is a market place in the trade of Brent crude oil. Almost two-thirds of the oil in circulation is valued according to the Brent crude prices. The quality of WTI makes it a little bit more expensive compared to the Brent crude oil (Milonas and Henker, 2001: 23-36).

From an economic perspective, as a critical energy source, oil is needed to support the development of the countries. And the heavily industrialized countries perceive it as an irrevocable energy source since it provides the advantage to maintain their economic superiority and prosperity. Similar to other commodities, oil as well is dictated by the equilibrium of supply and demand. However, in addition, there are also other important factors impacting the availability of crude oil such as business cycles and natural changefulness or conflict of interest across states (Hamilton, 2014: 179-206). In the light of such a scarce and important energy source, decision-makers at the large scale do have to consider all the possibilities to reach the greater good for the societies that they are part of.

On the financial side, oil prices constitute one of the most crucial financial time series which are extensively disclosed in the media all over the world. They are tracked by almost everyone since it will one way or the other has the possibility to impact their lives. Yet, there are different kinds of oil prices fixed every day. Methodologically, the examination and the interpretation of oil prices are rather obvious according to the studies put forth previously. In the estimation or the determination of the trend and behavior; countries, households and would be employed as explanatory variables in the models. In addition to the North Europe side, OPEC countries and Americas are the other prominent oil suppliers. It is no surprise that any change in the politics of the member states would result in a parallel alteration in the walk of the series.

As per the below graph, Brent crude oil prices wandered around a mean of $70 per barrel in 2018. This number realized as $17 p/b above the average of 2017 on annual basis which was $54 and just below the price of April 2018. According to the report distributed by the U.S Energy Information Administration, it is expected that Brent spot prices will be about $70-71 per barrel at the end of 2019. The respective forecast also expanded to include the possible 2020 prices which are considered $67 per barrel. It is seen that both the estimations reveal more strict anticipated demand for crude oil despite the rising risk of procurement interruption on a global scale. So far, the price differences of Brent crude oil and other alternatives were rooted in the variations of the characteristics of the product as well as the supply and demand imbalances to one another. After 2010 out of the ordinary, the price difference among Brent crude, West Texas Intermediate, and OPEC basket reached out averagely $12 per barrel one of the biggest differences. This deviation was navigating on around $3 per barrel prior to 2010. As of 2010 despite WTI is a more qualified product, Brent crude is being valued over the WTI for several causes which were tried to be clarified so far. Lastly, the depletion of the North sea oil fields is one of the other definements for the discrepancy which also can be observed in the futures indication traded over the counter markets.

Figure 6: Brent Crude Oil Prices($/PB, 1988-2018)



Source: FED of St. Louis, 2019

1.3.1 Demand for Crude Oil

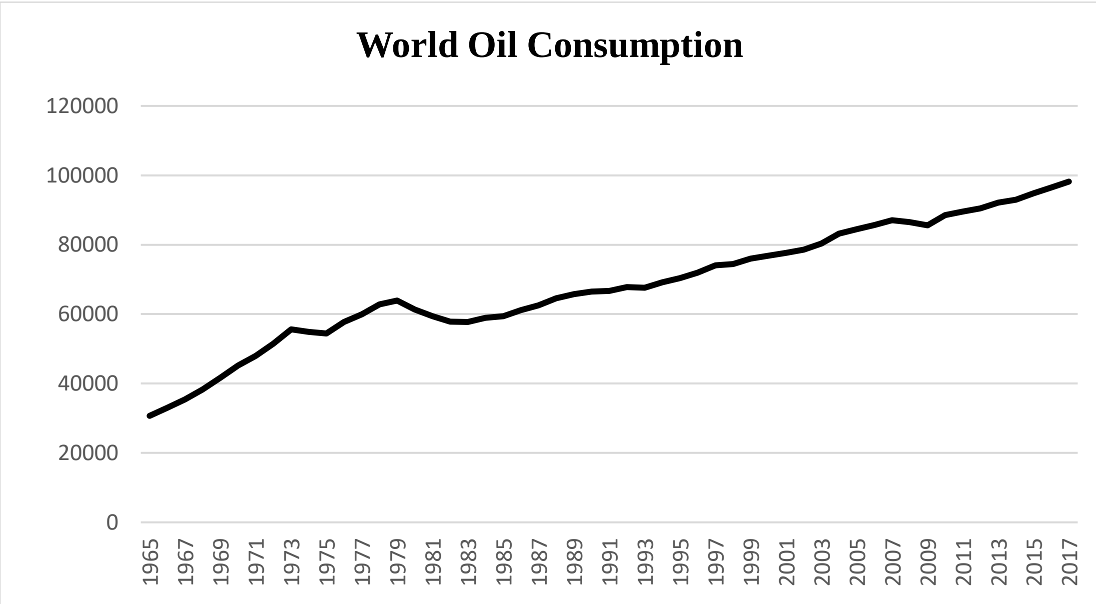
The demand for oil is a combination of actual aggregate demand, inventory balance and speculative attempts (Noreng, pp.1036-1038). According to U.S. Energy Information Administration report disclosed in the last quarter of 2018, energy usage is steadily expanding. Without a doubt the economic growth rate of the world along with the support of also emerging countries plays a very critical role in the subject rise (Mitchell et al., 2013: 1-286).

Since all sorts of underground sources are prominent influencers of industrialized economies. Hence, as the economic operations increase, the demand for particularly oil and to its transportation is also growing. What is more, the emerging countries are expected to be in need of energy sources more than ever before during the years to come until they level off. On the Asia side, China and India come forward to look for additional energy resources that put tremendous pressure over the oil prices considering the volume and pace of these economies. Oil-importing countries such as the U.S.A. is also going to increase their oil consumption by virtue of economic expansion to meet the aggressive attacks from the countries specified above. In the oil-exporting countries, on the other hand, are likely to observe a parallel growth in their oil sector to meet the aggregate demand and consequently this circumstance will be reflected in their GDP as growth. Convenient examples of these countries could be Russia and Saudi Arabia. In such countries, energy resources are seen a major source of income since their economy is heavily based on these extraction and sales operation. However, there is a controversy between the economies with different characteristics that when the oil prices are increasing, this situation becomes desirable by the economies in the export side. As a result, increasing cost of energy will lead to production cut and disemployment if the updated product costs could not be successfully reflected to the ultimate consumers. Demand on oil is also influenced by macroeconomic factors such as population and the current exchange rates varying from country to country since there is positive correlation between these indicators and oil prices. The oil demand of the world is now forecasted to rise by 1.50 million barrels per day (Mb/d) in 2018. Total global oil consumption the other hand is predicted to be in the neighborhood of 98 Mb/d for the same year. Demand growth in the oil for the OECD area is estimated to be kept unchanged compared to last month with OECD America expected to lead growth in 2018 in return for the robust demand to light and middle distillates. Solid macroeconomic indicators in the U.S. spurred diesel requirements while expansions of production in cracking capacities in the U.S. supported demand for NGLs/LPG. The OECD region is projected to increase imperceptibly comparing to 2018 at 50 thousand barrels per day, whereas oil demand in Asia Pacific is anticipated to decline. In the non-OECD region, oil demand increase was also left relatively similar to last month's expectations. Other Asia is forecasted to pioneer the increase in demand in 2018 globally, increasing by 0.44 Mb/d, after strength in product demand growth in India, Indonesia, Singapore, and Thailand was observed throughout 2018. In addition to that, demand in the Middle East and South America softened to 20 TB/d and negative 60 TB/d, respectively, due to economic slowdown and various reforms, including subsidy removals, substitution plans, and efficiency-related policies. By the end of 2019, world oil demand is predicted to increase about 1.29 Mb/d to a mean of 100.08 Mb/d, identical to the previous term's report. In the OECD region, oil demand is told to expand by 0.25 Mb/d, with OECD Americas is rigidly strongly driven by Natural Gas Liquids and middle distillate specifications. As for non-OECD area, subject increase is expected to be roughly 1.04 Mb/d with slightly lower than Chinese oil demand growth comparing to 2018; however, this growth is balanced by higher oil prerequisites in other regions such as Latin America and the Middle East as compared to 2018 estimates.

When we carefully review the below graph, it is clearly seen how a path traced the increase in oil demand on a global scale. While total crude oil demand globally (including biofuels) was in the neighborhood of 30 million barrels per day in 1965, yet it has seen the levels of 99.2 million barrels per day in 2018. By comparison with the daily oil demand in the amount 86.4 m/b in 2010, the rising demand path is obvious. However, it is absorbing to observe a consumption surge throughout the Far-East area which is principally directed by the excess demand of China. As witnessed in China, the aggressive economic growth of this specific country surges the energy use to meet its capacity requirements along with the magnitude of this rise also is subject to China's transition speed to a more focused in services and individual consumption-centered economy. If China does not follow the path to a more service-oriented economy, then implied energy demand rises by 25%

relative to the report issued by EIA 2018 in 2040, In case the other scenario is realized, then increase is forecasted to around 20% as the services will need less energy comparing to a heavy industrialized economy. In both cases, the country obviously stands out as the biggest manufacturer of energy-oriented products by 2040. In the same region, India is expected to have the world's largest population and the fastest-growing economy over the projection period. However in India's case; total energy use and energy use per capita will be lower than in China and the United States, taking third place over the next two decades. When we make a comparison as to the prospective paths to be taken by India like China, it is estimated that India's industrial sector is still the biggest energy-consuming sector over the period in concern for all India side cases as reviewed in the report. Lastly higher growth in Africa results in a rise in the production and parallelly an increase in its industrial oil consumption due to likely regional competitive edges. Forecasted economic growth above the mean, over the estimation period considering 2040, causes Africa centered energy demand per capita to be 25-30% up, relative to 2018, yet as clear, still lower levels than many other emerging countries such as China, India, and Brazil.

Figure 7: World Crude Oil Consumption (Yearly, 1965-2018)



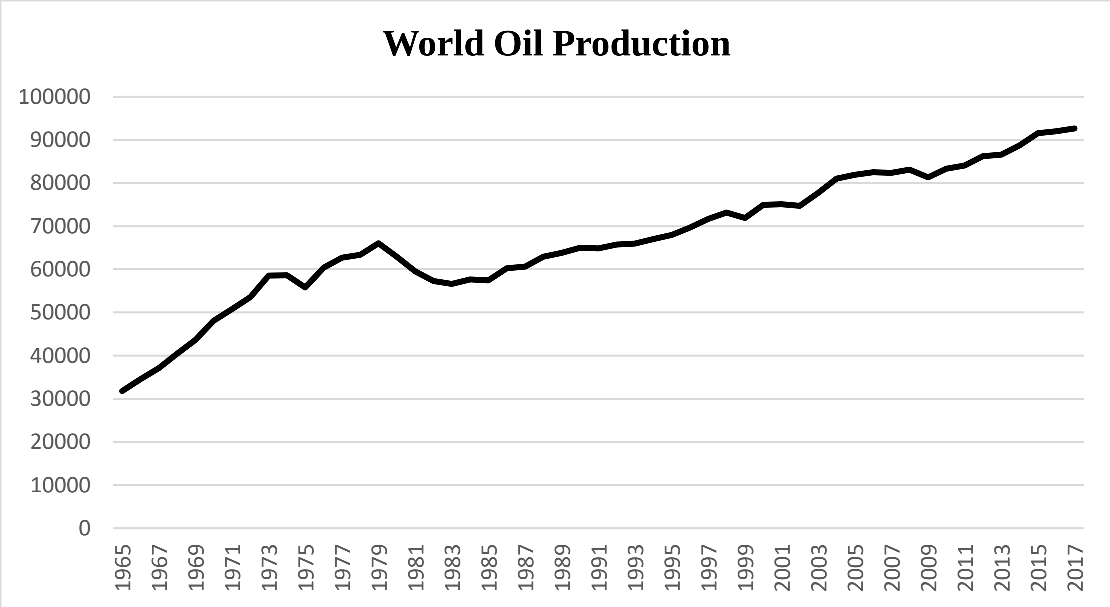
Source: British Petroleum, 2019 Volume: Thousand Barrels Per Day

1.3.2 Supply of Crude Oil

The oil supply is designated by the authenticated oil reserves, their growth rate and the predictions of the unexplored or nonconventional reserves (Banks, 1980). We can make inferences by looking at the authenticated oil reserves and decide the level of oil spread arouınd the World. Yet, for this estimation to be logical, the reserves available also must be feasible to extract. The increased pace of authenticated reserves is considered representative as to developments in the acquisition phases of the explored reserves. The growth rate is affected as well as identified by technological changes that improve oil acquisition that assists in maximizing the level of oil outturned from the fields. (Mitchell et al.,pp.1-286).

The oil industry is generally broken down into three main components: upstream, midstream and downstream. Firstly, the upstream sector is widely known in the oil sector as exploration and production (E&P). The upstream sector mainly involves the exploration and drilling of wells in underground or underwater crude oil and gas, drilling operations, recovery and well operations. The upstream sector has also undergone various developments in line with liquefied natural gas (LNG) operations and transportation developments so that there has been a dramatic crossing towards natural gas. The upstream industry has also been the most common component of mergers, acquisitions, and numerous liquidations. Secondly, “the Midstream sector deals with storage, transportation (by pipeline, rail, barge, oil tanker or truck) and wholesale marketing of crude or refined petroleum and petroleum products in the oil industry”. Midstream generally carries out its activities to cover some elements of the upstream and downstream sectors. For example, workers in the midstream sector can contribute to natural gas or oil processing as well as the extraction activities. Lastly, the workers in the downstream sector are widely involved in the refining and refining of crude oil, as well as in the distribution and marketing of crude oil products. Downstream sector employees have contributed to the production of numerous petrochemical products for consumers. Refining capacity, specifically in terms of distilling heavy crude to light crude, has been a subject discussed thoroughly. According to IEA 2019 report and as also seen from the below figure, the U.S. operable refinery capacity has not shown an upward trend since 1980. Finally, the annual average refining capacity in the U.S. is 17 million barrels per day in 2018, while the annual consumption was 99.2 million barrels in the same year. Refining of petroleum might be a problem needs to be resolved in the industry as petroleum stocks continue remaining at low levels and refinery utilization is high. World oil production graph is depicted below,

Figure 8: World Crude Oil Production (1965-2017)



Source: British Petroleum, 2019 Volume: Thousand Barrels Per Day

According to British Petroleum (BP) 2018, World Energy Statistics Outlook and previous years' reports, US oil and petroleum products production again took place at the summit last year. With the increase in crude oil prices last year, US oil production rose by 5.6% in 2017 compared to the previous year and was at the top of the world with an average of 13.06 Mb/d. Since therefore, the U.S.A. became the world's biggest oil producer and for four years in a row. In January 2017, with the intention to diminish the excess supply in the global oil market, Saudi Arabia and Russia, which cut their crude oil production levels, fell in oil production last year. Saudi Arabia's crude oil and petroleum production declined by 3.6 percent year-on-year to 11.95 million barrels per day last year, while the country ranked second in the world. Total oil production decreased by 0.1 percent compared to the previous year last year, an average of 11.26 million barrels per day in Russia in this area was the third in the world. On the other hand, “the United States has not abandoned its leadership in global oil consumption since 1965 when BP oil data began to be collected."

2.1 Historical Development of the Models

Despite the relatively short history of variance (ARCH) models in the autoregressive conditional environment, the relevant literature has evolved at a prominent pace in this brief history. Engle's original ARCH model, which is a major breakthrough, and its various adaptations have so far been applied to the various economic and financial time series of many countries. Although the awareness of the changing variance problem before finding the ARCH models, this specific issue has been tried to be overcome by using the processes that do not depend on a particular model. Mandelbrot (1963) aimed to cope with the repeated estimates of variance over time whereas Klein (1977) tried to deal with the variance problem, using the five-term moving variances of the ten-period moving sample average. The financial time series poses an array of general properties. It has been observed that the financial asset prices were generally non-stationary, asset yields were stable and did not show autocorrelation characteristics. Financial asset returns are prone to be leptokurtic. These mentioned yield distributions are more compact than normal distribution and have wider queues. This indicates that the probability of demonstrating large changes in financial time series is higher than normal distribution. Another phenomenon as remarked by Mandelbrot (1963) is volatility clustering. "The term volatility clustering means that large price changes in financial markets will be followed by large price changes and small price changes will be followed by small price changes." Finally, market participants in financial markets behave differently against good and bad news. Bad news is detected to create more volatility in proportion to good news. Therefore, the direction of the change in financial asset prices leads to an asymmetric effect on volatility. The ARCH model proposed by Engle (1982) has taken its place in history as the first formal model to take into account the empirical findings of financial asset returns. The ARCH model is of value not only because it takes into account some of the empirical findings of financial asset returns, but also because it finds itself ground in the applications of different areas and subjects. Bollerslev (1986) put forth the "Generalized

Autoregressive Conditional Variance (GARCH)" model by modeling the conditional variance as an extension of the "ARCH" model. The "GARCH" model is preferred to the ARCH model in terms of parameter compliance. Engle et al. (1987) at a later study manifested the ARCH-M method on average by including conditional variance as a descriptive variable for the mean equation. This approach is important in terms of testing the relationship between uncertainty and return that holds an important place in the theory of finance.

Univariate ARCH and GARCH approaches are criticized for not taking into consideration the time dependence between conditional variance and covariance among various markets and entities. To explain the said time dependence, Bollerslev et al. (1988) extended the "GARCH" model to multivariate dimension by means of VEC parameterization. However, because of the "VEC-GARCH" model has a large number of parameters estimates and the restriction of becoming bigger than zero of the covariance matrix is not possible at all times, leading to some challenges in terms of applicability. Bollerslev (1990) suggested the "Constant Conditional Correlation GARCH (CCC-GARCH)" model, where the number of parameters is considerably reduced and the forecast process is highly simplified when conditional correlations are constant. Contrary to the common assumption in the literature, Engle (1982) has proved by analyzing some macroeconomic data that the variance of error terms in time series models are time-varying. He explored that the large and small estimation errors spring in clusters in inflation models, and consequently the variance of estimation errors relies on the magnitude of previous period error terms. Engle indicated that the autocorrelation encountered in time series data and especially in predictions should be modeled with a technique called ARCH.

2.2 Univariate Heteroskedasticity Models

Uncertainty and risk concepts are at the center of modern economic theory. While the problem of heteroskedasticity is known as a problem in the horizontal cross-sectional data, it has also been observed that error variance can change over time in econometric models aiming to estimate financial time series. However, as stated previously, also important to stress again, it is presumed that error variance does not display any change over time in conventional time series models.

In the case of a variance problem in a traditional time series approach, "the Ordinary Least Squares (OLS)" estimator maintains the features of deviation and consistency. On the other side, in a model with heteroskedasticity problem, the efficiency of the model is lost and consequently the parameter estimation can become statistically insignificant. In order to eliminate this problem, models that allow variance and covariance to change over time have been proposed. In this regard, the Autoregressive Conditional Variable Variance (ARCH) model of which the details will be comprehensively and step by step discussed in this chapter.

2.2.1 Autoregressive Conditional Heteroskedasticity

Conditional Changing Variance Models were first introduced into the literature by Robert F. Engle (1982). Traditional time series approaches work with the assumption of time-independent constant variance. However, many time series, especially financial time series, do not meet this assumption. Conditionally varying variance models are parametric methods used to model risk-related volatility in financial literature at this point.

Engle (1982) argued that the variance of error terms u_t at the time of "t" was successively dependent (autocorrelated) on the variance of u_t in the previous periods and developed the ARCH model, unlike the assumption that error terms in traditional time series methods had constant variance.

The basic notion of "ARCH" is that the variance of u in the time t (σ_t^2) is dependent on the u_{t-1}^2 which becomes the square of the error term in the period (t-1).

In general, a process of autoregressive moving averages ARMA (p, q) is expressed as follows.,

$$\boldsymbol{y}_t = c + \sum_{i=1}^{p} \theta_i y_{t-i} + \sum_{i=1}^{q} \phi_i u_{t-i} + u_t \tag{1}$$

This model is called the conditional mean equation. It is assumed that the error terms u_t obtained from equation (1) are distributed normally with conditionally zero mean and variance ($\omega + \alpha_1 u_{t-1}^2$) in (t-1) period.

$$u_t \approx N[0, (\omega + \alpha_1 u_{t-1}^2)] \tag{2}$$

In equation (2), this process is named the ARCH (1) process since the variance of u_t depends on the square of the error term of the time preceding it. This process (Conditional variance) is shown as follows,

$$\boldsymbol{h}_t = Var(u_t) = \sigma_t^2 = V\left(\frac{u_t^2}{I_{t-1}}\right) = \omega + \alpha_1 u_{t-1}^2 \tag{3}$$

where I_{t-1} shows all the information available at (t - 1) and V value shows the "conditional variance of error terms". As it is seen, the importance of the equation is that it allows parametric modeling of conditional variance of error terms. Thus, new information obtained for estimating financial data affects variance or volatility can be modeled. Accordingly, it can be inferred how volatility changes over time. Via equation (3), the unexpected development values in financial asset returns can be determined. According to that model, the conditional variance is defined as a function that depends on the square of unexpected error terms (shocks, news or surprises).

The ARCH (1) process as a general ARCH (q) process is designated as follows,

$$\begin{aligned} \boldsymbol{h}_t = Var\left(u_{tq}\right) = \sigma_t^2 &= w + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \cdots + \alpha_q u_{t-q}^2 \\ &= \omega + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 \end{aligned} \tag{4}$$

with;

$$\omega > 0\,;\ \alpha_i \geq 0\,;\ and\ \sum_{i=1}^{q} \alpha_i < 1$$

Before applying the ARCH method, it is a requirement to test if there is any ARCH effect or not. The two most important tests to examine the existence of ARCH effect are Engle's (1982) “ARCH-LM” test and the Q test which belongs to McLeod Li’n (1983). In practice, the ARCH-Lagrange Multiplier test is preferred among the squared errors of the model. The ARCH-LM test squaring of the error terms obtained from Equation (5) is modeled as in Equation (6).

$$y_t = C + \theta_1 y_{t-1} + \theta_2 y_{t-2} + \cdots + \theta_p y_{t-p} + u_t \tag{5}$$

$$\hat{u}_t^2 = C + \alpha_1 \hat{u}_{t-1}^2 + \alpha_2 \hat{u}_{t-2}^2 + \cdots + \alpha_q \hat{u}_{t-q}^2 + v_t \tag{6}$$

“In the alternative hypothesis, the detection of the presence of the ARCH effect is tested against H_0 which states that the errors have a white noise process, and the alternative hypothesis indicating the existence of errors with the ARCH effect (Sevüktekin ve Nargeleçekenler, 2010: 243-265).”

$$H_0 = \alpha_1 = \alpha_2 = \cdots = \alpha_q = 0 \tag{7}$$

$$H_1 = at\ least\ one\ \alpha_i > 0 \tag{8}$$

2.2.2 Generalized AutoRegressive Conditional Heteroskedasticity

GARCH models developed by Bollerslev (1986), which expresses the expanded version of the ARCH models, are the volatility models in which conditional variance is dependent on its lagged values in addition to the lagged values of the error term. This model is the weighted average of past residual squares. Yet, it possesses decreasing weights that never converge utterly to zero.

$$\boldsymbol{h}_t = \omega + \sum_{j=1}^{p} \beta_j h_{t-j} + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 \tag{9}$$

with,

$$\omega > 0 \; ; \; \alpha_i \geq 0 \; ; \; \beta_j \geq 0$$

and

$$\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1$$

Maximum Likelihood method is adopted to estimate the parameters in the equation. GARCH (1,1) $(h_t = \omega + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1})$ is the most widely and accepted model used for estimating volatility in practice. In addition, this approach is considered adequate to clarify the characteristics of econometrics and financial time series (Hansen and Lunde, 2005: 873 - 889). In addition, when $p = 0$, GARCH (p, q) is reduced to ARCH (q) and u_t will be "white noise" process while $p = q = 0$. In terms of the effectiveness of the model; after writing the conditional variance equation, two conditions are searched for the parameters of the estimated "ARCH" and "GARCH" model. The first is that the constant-coefficient to the right of the conditional variance equation is bigger than zero $(\omega > 0)$ and the coefficients of other variables $\left(\alpha_i \geq 0; \; \beta_j \geq 0; i = 1,2, \ldots, q\right)$are greater than or equal to zero so that the variance known as non-negative becomes positive. The second condition is the stationary condition for autoregressive models. In order to maintain stationary, the sum of all the parameters except the constant to the right of the conditional variance equation must be less than one.

2.3 Multivariate Heteroskedasticity Models

Since the volatility modeling of a single series is inadequate when considering financial practices, it may be of interest to examine the volatility of multiple series simultaneously, as well as to examine their correlations, which requires the use of multivariable GARCH (MGARCH). There are several proposed methods for MGARCH modeling. In fact, their common feature is that they first estimate the volatility and then estimate the correlations with additional parameters.

In spite of the challenges we might come across an exactly multivariate GARCH approach, its reward is evident in terms of the questions that sort of approaches make it possible to answer, besides whether or not correlations vary over time: Does the volatility of one specific market spread over the volatility of other markets? Is the volatility of an asset propagated to another asset straight-forwardly (via its conditional variance or correlations) or implicitly?

In this section, we will discourse the significant analysis between passive and active risk management that encourages the need for a multivariate scope to the time series analysis of volatility and covariance.

2.3.1 VEC-GARCH Model

In the Vec parameter proposed by Bollerslev, Engle, and Wooldridge (1988), conditional variance assuming no external effects is described as follows,

$$vech\,(\boldsymbol{H}_t) = \boldsymbol{\omega} + \sum_{j=1}^{q} \boldsymbol{A}_j vech\big(\varepsilon_{t-j}\varepsilon'_{t-j}\big) + \sum_{j=1}^{p} \boldsymbol{B}_j\, vech\big(H_{t-j}\big) \tag{10}$$

"where vech(·) represents the column stacking the lower triangular portion (unique elements) of a N×N matrix as a N(N + 1)/2 × 1 vector. $\boldsymbol{A_j}$.and.$\boldsymbol{B_j}$.are N (N+ 1)/2 × N(N +1)/2 parameter matrices."

A two-variable VEC-GARCH (1,1) model, which does not have external effects, is expressed in the matrix form as follows,

$$\boldsymbol{h}_t = \begin{bmatrix} h_{11,t} \\ h_{12,t} \\ h_{13,t} \end{bmatrix}$$

$$= \begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} \mathcal{E}^2_{1,t-1} \\ \mathcal{E}_{1,t-1}\mathcal{E}_{2,t-1} \\ \mathcal{E}^2_{2,t-1} \end{bmatrix}$$

$$+ \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \begin{bmatrix} h_{11,t-1} \\ h_{12,t-1} \\ h_{22,t-1} \end{bmatrix} \tag{11}$$

The likelihood function of the VEC-GARCH model, with condition that errors z_t has a multivariate normal distribution is stated as,

$$\sum_{t=1}^{T} \ell_t(\boldsymbol{\theta}) = c - \frac{1}{2}\sum_{t=1}^{T} \ln|H_t| - \frac{1}{2}\sum_{t=1}^{T} \mathcal{E}_t' H_t^{-1} \mathcal{E}_t \qquad (12)$$

Here $\boldsymbol{\theta}$ includes all parameter vectors in the regression model and is estimated iteratively. In all iterations, it is necessary to reverse the "conditional covariance matrix" for all t values, which results in a heavy operational load. Another challenge is the positive identification of the covariance matrix.

2.3.2 BEKK-GARCH Model

Due to the problems of excess parametrization in the "VECH-GARCH" model, Baba, Engle, Kraft, and Kroner have proposed the BEKK notation, which is referred to by their initials and ensures lower parameters with positive definiteness (Engle and Kroner, 1995). Again, assuming that there are no external influences, BEKK representation of $\boldsymbol{H}_t$ is as follows:

$$\boldsymbol{H}_t = \boldsymbol{C}\boldsymbol{C}' + \sum_{j=1}^{q}\sum_{k=1}^{K} \boldsymbol{A}_{kj}' E_{t-j} E_{t-j}' \boldsymbol{A}_{kj} + \sum_{j=1}^{p}\sum_{k=1}^{K} \boldsymbol{B}_{kj}' \boldsymbol{H}_{t-j} \boldsymbol{B}_{kj} \qquad (13)$$

In the above equation; conditional.variance.is $\boldsymbol{A}_{kj}$., $\boldsymbol{B}_{kj}$ which is "*N x N* parameter matrices" and $\boldsymbol{C}$ is a lower triangular matrix. As $\boldsymbol{CC'} > 0$, $\boldsymbol{H}_t$ matrix will be positively defined if the matrix $\boldsymbol{H}_0$ is defined positively.

If to be expressed in matrix form, for N = 2 and K = 1 BEKK-GARCH (1,1) model would be;

$$
\begin{bmatrix} h_{11,t} & h_{21,t} \\ h_{21,t} & h_{22,t} \end{bmatrix}
= \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix} \begin{bmatrix} c_{11} & c_{21} \\ 0 & c_{22} \end{bmatrix}
+ \begin{bmatrix} a_{11} & a_{21} \\ a_{12} & a_{22} \end{bmatrix} \begin{bmatrix} \mathcal{E}_{1-t-1}^2 & \mathcal{E}_{1,t-1}\mathcal{E}_{2,t-1} \\ \mathcal{E}_{2,t-1}\mathcal{E}_{1,t-1} & \mathcal{E}_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}
+ \begin{bmatrix} b_{11} & b_{21} \\ b_{12} & b_{22} \end{bmatrix} \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22-t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \tag{14}
$$

The simplified version of the BEKK-GARCH model is the diagonal BEKK-GARCH (DBEKKGARCH) model, which assumes the $\boldsymbol{A}_j$ and $\boldsymbol{B}_j$ matrices are diagonal. Even if the positive definition of the $\boldsymbol{H}_t$ matrix is provided, the estimation of the BEKK-GARCH model continues to have an operational challenge due to several parameterizations that yield the same representation of the model. Parameters to be estimated are ((p + q) KN^2 + (N × (N + 1) / 2)) and ((p + q) KN + (N × (N + 1) / 2)) in the BEKK-GARCH model and the diagonal BEKK-GARCH model respectively. Because of the operational difficulty of estimating a large number of parameters, empirical applications usually take p = q = K = 1.

2.3.3 Models of Conditional Variances and Correlations

The parameters that model conditional correlations of “multivariate GARCH models” are defined according to whether the conditional correlations are constant or dynamic. Two different parametrizations are recommended for dynamic conditional correlations. The simplest version of such approaches is the “Constant Conditional Correlation GARCH (CCC-GARCH)” model introduced by Bollerslev (1990). In the said equation, the “conditional correlation matrix” is assumed to be not changing even if the time changes. Accordingly, “the conditional covariance matrix” will be described as follows;

$$
\boldsymbol{H}_t = \boldsymbol{D}_t \boldsymbol{P} \boldsymbol{D}_t \tag{15}
$$

where,

$$\boldsymbol{D}_t = diag\left(h_{1t}^{\frac{1}{2}}, \dots, h_{Nt}^{\frac{1}{2}}\right) \text{ and, } \boldsymbol{P} = \left|\rho_{ij}\right| \tag{16}$$

with $\rho_{ii} = 1, i = 1, \dots, N$

An explanation to above would be that the "off-diagonal elements of the conditional covariance matrix" are determined as per below;

$$[\boldsymbol{H}_t]_{ij} = h_{it}^{\frac{1}{2}} h_{jt}^{\frac{1}{2}} \rho_{ij}\ , \quad i \neq j \quad \text{with } 1 \leq i, j \leq N \tag{17}$$

Generally, conditional variances are modeled as the "GARCH (p,q)" model in which case "the conditional variances" can be displayed in a vector form as follows;

$$\boldsymbol{h}_t = \boldsymbol{\omega} + \sum_{j=1}^{q} \boldsymbol{A}_j \mathcal{E}_{t-j}^{(2)} + \sum_{j=1}^{p} \boldsymbol{B}_j h_{t-j} \tag{18}$$

where $\boldsymbol{\omega}$ is a N x 1 vector, $\boldsymbol{A}_j$ and $\boldsymbol{B}_j$ are diagonal N x N matrices and $\mathcal{E}_t^{(2)} = \mathcal{E}_t \odot \mathcal{E}_t$

In this model, if "the conditional correlation matrix" $\boldsymbol{P}$ and the diagonal elements of $\boldsymbol{\omega}$ and $\boldsymbol{A}_j$ and $\boldsymbol{B}_j$ matrices are greater than zero, the conditional covariance matrix $\boldsymbol{H}_t$ is also positive.

The "CCC-GARCH" model is not considered a realistic model because it is based on a constant conditional correlation assumption. In this context, the model has been developed to permit a structure where the conditional correlation matrix can take different values depending on time. Thus,

$$\boldsymbol{H}_t = \boldsymbol{D}_t \boldsymbol{P}_t \boldsymbol{D}_t \tag{19}$$

Tse and Tsui (2002) suggested the "Varying Correlation GARCH (VC-GARCH)" model in which "the conditional correlation matrix" followed the GARCH process. According to that model, the "conditional correlation matrix" is expressed as follows;

$$\boldsymbol{P}_t = (1 - a - b)\boldsymbol{S} + a\boldsymbol{S}_{t-1} + b\boldsymbol{P}_{t-1} \tag{20}$$

Here, $\boldsymbol{P}_t$ is a.function of $\boldsymbol{P}_{t-1}$ and a group of estimated.correlations. S diagonal elements show a positive defined constant matrix consisting of ones, while a.and.b are positive scalar values under the condition that $(a + b) \leq 1$. When the $\boldsymbol{P}_0$ and $\boldsymbol{S}_{t-1}$ matrices are bigger than zero. Thus, conditional correlation matrix also becomes positive.

Christodoulakis & Satchell (2002), Engle (2002) and Tse & Tsui (2002) have transformed the “CCC-GARCH” model in which “the conditional correlation matrix” is contingent on the time. This leading-edge model is named “Dynamic Conditional Correlation GARCH (DCC-GARCH)” model and has a “dynamic conditional correlation” structure and is homogeneous of the “VC–GARCH” model. The model suggested by Christodoulakis and Satchell (2002) can only be applied to bivariate models. On the other hand, the “DCC-GARCH” model suggested by Engle (2002) and Tse & Tsui (2002) can be applied for multivariate and high dimensional data sets. Engle considered a dynamic matrix process as;

$$\boldsymbol{D}_t = \begin{bmatrix} \sqrt{h_{1,t}} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sqrt{h_{N,t}} \end{bmatrix} \tag{21}$$

and,

$$\boldsymbol{P_t} = (\boldsymbol{I} \odot \boldsymbol{Q_t})^{-\frac{1}{2}}\boldsymbol{Q_t}(\boldsymbol{I} \odot \boldsymbol{Q_t})^{-\frac{1}{2}} \tag{22}$$

and,

$$\boldsymbol{Q_t} = (\boldsymbol{1} - \boldsymbol{a} - \boldsymbol{b})\boldsymbol{S} + \boldsymbol{a}\boldsymbol{Z_{t-1}}\boldsymbol{Z'_{t-1}} + \boldsymbol{b}\boldsymbol{Q_{t-1}} \tag{23}$$

$$\boldsymbol{Z}_{i.t} = \frac{\mathcal{E}_{i,t}}{\sqrt{h_{i,t}}} \tag{24}$$

where “a” is positive and “b” is non-negative scalar parameters such that $a + b \leq 1$, and $\boldsymbol{S}$ refers to “the unconditional covariance matrix” of “the standardized errors $\mathcal{E}_t$“ and $\boldsymbol{Q}_0$ is positive definite.

$$\boldsymbol{S} = \frac{1}{T}\sum_{t=1}^{T}\begin{bmatrix} z_{1,t}^2 & z_{1,t}z_{2,t} & \cdots & z_{1,t}z_{N,t} \\ z_{2,t}z_{1,t} & z_{2,t}^2 & \cdots & z_{2,t}z_{N,t} \\ \vdots & \vdots & \ddots & \vdots \\ z_{N,t}z_{1,t} & z_{N,t}z_{2,t} & \cdots & z_{N,t}^2 \end{bmatrix} \tag{25}$$

Both the "Varying Correlation" and the "DCC–GARCH" models are the improved form of the "CCC–GARCH" model and the dynamic structure of the time-varying correlations is a function of past returns, however, it performs its duty with a few more parameters resulting in more robust outputs.

The estimation of MGARCH models with constant correlations is computationally attractive. Due to the decomposition, the log-likelihood takes the following clear form:

$$\sum_{t=1}^{T}\ell_t(\boldsymbol{\theta}) = c - \frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{N}\ln|h_{it}| - \frac{1}{2}\sum_{t=1}^{T} log|P| - \frac{1}{2}\sum_{t=1}^{T}\mathcal{E}_t' D_t^{-1}P^{-1}D_t^{-1}\mathcal{E}_t \tag{26}$$

In the context of MGARCH, basically, three fundamental models were discussed so far. "The VECH" model, which is a direct generalization of the univariate "GARCH" model to multi-dimensions. Afterward, "The BEKK" model of Engle and Kroner (1995), which reduces the parameter dimension of the VECH model and has the advantage that H_t is restricted to be positive definite at each "t" and the models of conditional variances and correlations followed. Lastly and especially "DCC" model of Engle (2002) is noteworthy which diminishes the dimension of the.unknown parameters of the BEKK model further, and this breakthrough leads the estimation of high dimensional multivariate "GARCH" models to be more productive.

3.1 Descriptive Statistics

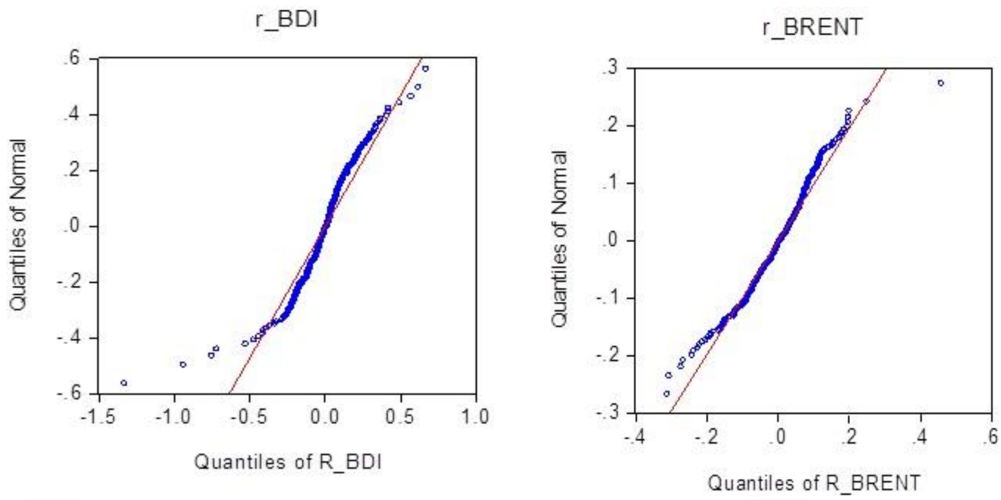
The present research study is conducted using the monthly indices for BDI and Brent crude oil prices. Monthly returns for BDI and Brent crude prices were constructed for the period January 1, 1988, to December 1, 2018 resulting in a total of 372 observations for each time series. Descriptive statistics were found to be as follows,

Table 1 Descriptive statistics of monthly returns for BDI and Brent Crude Oil

	R_BDI	**R_Brent Crude Oil**
Mean	-4.96e-05	0.003261
Median	0.009989	0.007962
Maximum	0.671069	0.458950
Minimum	-1.329792	-0.310955
Std. Dev.	0.187599	0.089914
Skewness	-1.309151	-0.198317
Kurtosis	12.40058	5.269414
Jarque-Bera	1476.011	82.26713
Probability	0.000000	0.000000
Sum	-0.018449	1.213197
Sum Sq. Dev	13.05676	2.999328

The first thing we can deduce from basic statistics shown above is the interpretation of Skewness which is an indicator of where the variable values observed in the data are concentrated on the right or the left around the mean. For both of the series, since "Skewness < 0 - left-skewed distribution - most values are concentrated on the right of the mean." And the other indicator Kurtosis is a concept of whether the graphical distribution of variable values observed in data is flat or peaked. In these statistics as the Kurtosis > 3 we can say that this is a Leptokurtic distribution(Fat Tail), sharper than a normal distribution, with values appear to be centered around the mean. This means that high probability for extreme values. And according to Jaque Berra test statistics H_0 which hold the distribution is normal is rejected for both the return series. Further visual information is provided through the following graphs showing the behavior of the respective data. In order to visualize the tail characteristics of our variables the respective Q-Q plots are provided as follows,

Figure 9: Q-Q Plots for the R_BDI and R_BRENT



.**Figure 10:** Return Series of Baltic Dry Index (1st Difference)

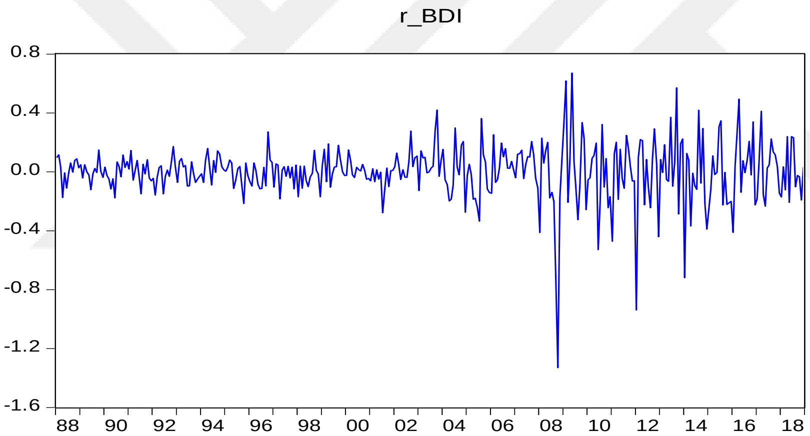
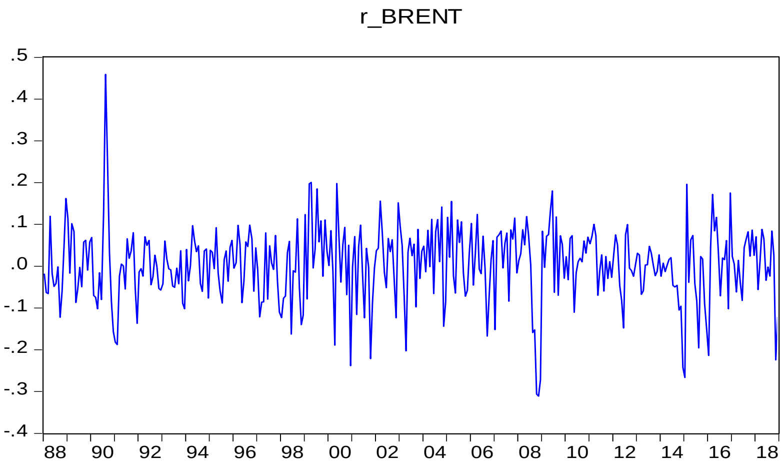


Figure 11: Return Series of Brent Crude Oil Price (1st Difference)



3.2 Heteroskedasticity Diagnosis

The existence of the GARCH structure can be tested with the LM test which follows the same logic as the diagnosis of the ARCH structure. In this context, Table 2 shown below designate the ARCH-LM test results for which the regression equation is;

$$e_t^2 = \beta_0 + \left(\sum_{i=1}^{q} \beta_i e_{t-i}^2 \right) + u_t \tag{27}$$

e is the residual and q is the order of the regression.

Modeling Volatility Linkages Between Baltic Dry Index and Oil Prices

Table 2 ARCH-LM test statistics of monthly returns for BDI and Brent Crude Oil

	R_BDI	**R_Brent Crude Oil**
F-Statistic	6.599445	29.03357
Probability	0.0106	0.000000

Null.hypothesis in.”ARCH-LM” test is ARCH up to order q can not be detected in the residuals. Therefore it is obvious of foregoing Table 2 that the null hypothesis expressing equal variance will be rejected. In other words, there is an ARCH effect and this effect should be eliminated. After accepting the existence of the ARCH effect, an appropriate ARCH type model was chosen. Concordantly, various MGARCH models have been tried and related results are given in chapter 4.

3.3 Unit Root Tests

Many studies dealing with time series require that the variables used to be subjected to stationarity tests. In order to comprehend the dynamics underlying the changes in the time series in our study, we carried out the ADF test. Dickey-Fuller unit root test is the most widely accepted stationarity determination way in the literature. In this section we will handle the stationarity characteristics of the respective series.

Modeling Volatility Linkages Between Baltic Dry Index and Brent Oil Prices

Table 3 Unit root test statistics of monthly returns for BDI and Brent Crude Oil

Augmented Dickey-Fuller Test	**R_BDI**	**R_Brent Crude Oil**
F-Statistic	-16.81642	-14.58393
Probability	0.0000	0.0000
Test Critical Values		
1% Level	-3.447770	-3.447770
5% Level	-2.869113	-2.869113
10% Level	-2.570871	-2.570871

According to the above test results, it is obvious that we do not have any stationary problem at all significance levels. Thus, we can reject the null hypothesis stating that the series in concern have unit-roots.

4.1 DCC-GARCH Test Results

In this chapter, we will examine the test results of the variables for our alternative hypothesis stating that there is a volatility spillover from Crude Oil Prices to BDI in our study.

Modeling Volatility Linkages Between Baltic Dry Index and Crude Oil Prices

Table 4 MV-DCC GARCH with Spillover Variances

Estimation by BFGS GARCH(1,1) - DIST=T - ITERS=100

Variable	Coeff.	Std. Error	T-Stats	Signif
1. Mean (R_BDI)	0.275554533	0.008211866	33.55565	0.00000000
2. Mean (R_BRENT)	0.079943450	0.003448912	23.17932	0.00000000
3. C(1)	0.054720959	0.000891670	61.36905	0.00000000
4. C(2)	0.005126690	0.000333896	15.35418	0.00000000
5. A(1,1)	0.594309453	0.016568933	35.86890	0.00000000
6. A(1,2)	-0.029068124	0.000294612	-98.66584	0.00000000
7. A(2,1)	0.073906856	0.001849183	39.96731	0.00000000
8. A(2,2)	0.822750931	0.016528067	49.77902	0.00000000
9. B(1)	0.227753000	0.024531963	9.28393	0.00000000
10. B(2)	0.122280709	0.034768087	3.51704	0.00043639
11. DCC(A)	0.028876107	0.000471095	61.29568	0.00000000
12. DCC(B)	0.125169913	0.011912713	10.50725	0.00000000
13. Shape	1.974390021	0.069730974	28.31439	0.00000000

Despite there are many alternative approaches in the literature in the context of MGARCH, DCC-GARCH (1,1) method, which is found to provide the most statistically significant results after heuristic approach, is used in this study and the results related to the above-mentioned relationships are presented. When the estimation results were examined, it was observed that the regression coefficients were statistically significant at 1% significance level. The DCC-GARCH (1,1) model assumes that the conditional correlation between the two return series changes over time. Two-step procedure.is used to estimate.the “DCC-GARCH” model. Initially, a univariate GARCH (p, q) model is estimated for each return series within a multivariate system. In the second step, DCC parameters are estimated using standardized residues obtained in the first step. In the table above, Mean (R_BDI) and Mean (R_BRENT) refers to the mean in the AR model. The mean of the volatility model for each variable, which is ω in the literature, is represented by C1 and C2 for BDI and Brent oil prices respectively. The coefficients A(1,1) and A(2,2) represent the ARCH effect (the effect of shock) for each variable. A(1,2) expresses the volatility transmission.from the first variable to the second. Accordingly, when volatility in the BDI increases, volatility in Brent oil prices decreases because of the negative coefficient of -0.029068124 in the model. Parameter A(2,1) indicates the volatility transmission from the Brent oil price changes to the BDI. According to this parameter, since volatility transmission from Brent oil price fluctuations to the BDI is positive (0.073906856), volatility increases in BDI when volatility in Brent oil increases. B(1) and B(2) are the coefficients, which are β in the literature, of the lagged variance. In this regard, B(1) is the β for BDI and B(2) is the β of Brent oil prices in the univariate GARCH(1,1) model. In the literature, the volatility persistence is interpreted by taking the sum of A (α) and B (β) or only with the coefficient β. The α coefficient is interpreted as short term shocks and the β coefficient is interpreted as a measure of long-term volatility persistence. For theoretically established GARCH (1,1) model, the sum of $\alpha + \beta$ should be less than 1. GARCH (1,1) coefficients are the key to volatility persistence and hence determination of macroeconomic risk. Volatility persistence is also important for many issues such as forecasting future market movements, risk management, pricing, and market efficiency. When DCC parameters, which are the indicators of spillover effect, are examined, DCC(A), which is the effect of common initial shock, can be interpreted by the coefficient of 0.028876107 that the effect of the past shocks on current conditional correlations is low. On the other hand, DCC(B), which is the coefficient of lagged conditional correlation matrix, is seen in the level 0.125169913. When we consider DCC(A) and DCC(B) as a whole, we can infer that compared to conditional past shocks, past correlations have more effect on current conditional correlations.

Additionally, $\frac{\ln(0.5)}{\ln(0.028876107+0.125169913)}$ gives us the persistence time of the common shocks.

If we are to elaborate further on parameter A(2,1), since the volatility transition is in the positive direction, we can also say that companies operating in the international maritime market taking position along with the direction of Brent oil prices in order to absorb the fluctuations. As for the A(1,2), when the volatility in the BDI increases, especially as the European countries direct their demand to Brent oil and this situation emerges as a factor that reduces the volatility of Brent crude oil. This is due to the fact that the price risks arising in the transportation industry of the European countries or the companies operating in Brent crude area are reflected in the transportation costs by means of demand increase of these countries or entities to the products of Brent oil derivatives. In other words, this parameter can also be defined as a measure of the substitution effect of transport costs in European countries. Finally, we will mention the shape parameter with the coefficient of 1.974390021. The shape parameter refers to the degree of freedom. As seen, it is statistically significant at 1% according to Student's t distribution. If the parameter coefficient was 2, it would mean symmetric distribution. Yet, since it was estimated less than 2, meaning that there is an asymmetric distribution with long-tail characteristics. This could also be observed with the Q-Q plots placed in the previous chapter where descriptive statistics were discussed.

4.2 Multivariate ARCH Test for Residuals

The multivariate ARCH test is a procedure for testing a set of series for multivariate ARCH effects. The null hypothesis is that the series is mean zero, not serially correlated and with a fixed covariance matrix and it performs a Lagrange Multiplier test by regressing the cross products of the on a constant and its lags in addition to testing the coefficients on the lags. In order to check if there is left any Arch effect on the residuals after employing our DCC-GARCH model, we carry out this test as another measure as to the robustness of our model. The respective test results on different lags are as follows,

Table 5 Multivariate ARCH test statistics on residuals

Lags	**Stats**	**Degrees**	**Significance**
5	58.01	45	0.09234
6	65.27	54	0.13993
7	72.88	63	0.18488
8	76.62	72	0.33271
9	81.01	81	0.47888
10	90.06	90	0.47850

As understood from the above table, the post-GARCH diagnostic cannot be detected meaning there is not left any Arch effect in the standardized residuals which makes our analysis statistically significant.

CONCLUSION

This study examined the dynamic relationships between the Baltic Dry Index and the Brent Crude Oil prices using daily data from 01 January 1988 to 01 December 2018. The primary purpose of the investigation was to explore the possibility of spillovers in returns and in conditional volatility across these two indices. The monthly return series consisted of 372 observations of each index that have been taken as data and were used in the constructed model. Before the model was established, respective literature was carefully reviewed and afterward comprehensive characteristics of each variable have been provided in the first chapter. Then, the heteroskedasticity models were discussed. Following the descriptive statistics of the data set were given, the ARCH effect in the return series was tested. And finally, the model was established and the results were interpreted. According to the findings obtained by DCC-GARCH model, the volatility transmission from Brent Oil Prices to the Baltic Dry Index was concluded to be statistically significant. In this regard, we cannot reject our alternative hypothesis stating that there is volatility transmission from oil prices to the BDI and also concluded that any fluctuation in the Brent Crude Oil Prices will affect the performance of the Baltic Dry Index and thereof the international trade. And the fact remains that this finding is only one side of the comprehensive volatility transmission realm, even for our variables in concern in the study, further studies can be carried out employing different algorithms or approaches. In recent years, especially machine learning and, as a type of ML, deep learning applications adopting various activation functions and their findings through different disciplines keep on capturing close attentions from various mediums.

REFERENCES

Bakshi, G., Panayotov, G., and Skoulakis, G. (2010). *The Baltic Dry Index as a Predictor of Global Stock Returns, Commodity Returns, and Global Economic Activity*, SSRN: https://ssrn.com/abstract=1747345, (24 March 2019).

Banks, F. (1980). *The Political Economy of Oil*, Toronto, Canada: Lexington Books.

Baltic Exchange, About Us, https://www.balticexchange.com/about-us/history/, (19 March 2019).

Bildirici, M. et al. (2015). Baltic Dry Index as a Major Economic Policy Indicator: The relationship with Economic Growth, *Procedia-Social and Behavioral Sciences*, 210: 416 – 424.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity, *Journal of Econometrics*, 31(3): 307-327

Bollerslev, T., et al. (1988). A Capital Asset Pricing Model with Time-varying Covariances, *Journal of Political Economy*, 96(1): 116-131

Bollerslev, T. (1990). Modeling the Coherence in Short-Run Nominal Exchange Rates: A Multivariate Generalized ARCH Model, *Review of Economics and Statistics*, 72: 498-505.

British Petroleum, *BP Statistical Review of World Energy* (2018), London: BP p.l.c

Christodoulakis, G.A., and Satchell, S.E. (2002). Correlated ARCH (CorrARCH): Modelling the Time-Varying Conditional Correlation Between Financial Asset Returns, *European Journal of Operational Research*, 139: 351-370.

Engle, R. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation, *Econometrica*, 50: 987–1006.

Engle, R and Granger, C. (1987). Co-integration and Error Correction: Representation, Estimation, and Testing, *Econometrica*, 55(2): 251-276.

Engle, R and Kroner, K. (1995). Multivariate Simultaneous Generalized Arch, *Econometric Theory*, 11(1): 122-150.

Engle, R. and Sheppard, K. (2001) Theoretical and Empirical Properties of Dynamic Conditional Correlation Multivariate GARCH, *University of California at San Diego*, NBER Working Paper, No:8554, National Bureau of Economic Research.

Fattouh, B., and Mabro, R. (2006). *Oil in the 21st century: Issues, challenges and opportunities*, New York, USA: Oxford University Press, 101-127

Fonshtain, T. (2009). *Behavioural Approach to Oil Price Dynamics*, Copenhagen: Copenhagen Business School.

Geman, H., Smith, W.O. (2012). Shipping markets and freight rates: an analysis of the Baltic Dry Index, *Journal of Alternative Investments*, 15(1): 98-109.

Goulielmos, M., and Psifia, M. (2006). Shipping finance: time to follow a new track?, *Maritime Policy & Management*, 33(3): 301-320.

Hamilton, J.D. (2014). Understanding Crude Oil Prices, The Energy Journal, *International Association for Energy Economics*, 30(2): 179-206.

Hornsell, P., and Mabro, R. (1993). *Oil Markets and Prices: The Brent Market and the Formation of World Oil Prices*, Oxford: Oxford University Press.

Hotelling, H. (1931). The Economics of Exhaustible Resources, *Journal of Political Economy*, 39(2): 135-79.

Jeantheau, T. (1998). Strong Consistency of Estimators for Multivariate Arch Models, *Econometric Theory*, 14(1): 70-86.

Klein, R. and Bawa, V. (1977). The effect of limited information and estimation risk on optimal portfolio diversification, *Journal of Financial Economics*, 5(1): 89-111

Koskinen, M., and Hilmola, O. (2005). Investment Cycles in the Newbuilding Market of Ice-Strengthened Oil Tankers, *Maritime Economics and Logistics*, 7(2): 173-188.

Koyfin, BDIY, https://www.koyfin.com/charts/g/BDIY# , (19 March 2019)

Mandelbrot, B. (1963). The Variation of Certain Speculative Prices, *The Journal of Business*, 36(4): 394-419.

Milonas, N., and Henker, T. (2001). Price spread and convenience yield behavior in the international oil market, *Applied Financial Economics*, (pp.23-36), London: Chapman & Hall.

Mitchell, J., et al. (2013). *The new economy of oil: Impacts on business, geopolitics and society*, London: Earthscan.

Mowry, B., and Pescatori, A. (2008). Industrial Production, Commodity Prices, and the Baltic Dry Index, *Economic Trends*, 8-12.

Möbert, J. (2007). Crude oil price determinants, Darmstadt: *Technische Universität Darmstadt Discussion Papers in Economics*, No. 186.

Nelson, D. (1991). Conditional heteroskedasticity in asset returns: A new approach, *Econometrica*, 59: 347–70.

Lin, F., and Sim, N. (2013). Trade, Income and the Baltic Dry Index, European *Economic Review*, 59: 1-18.

Noreng, Ø. (2002). Crude power: Politics and the oil market, *Elsevier,* 32(8): 1036-1038.

Notteboom, T., and Cariou, P. (2009). *Fuel surcharge practices of container shipping lines: Is it about cost recovery or revenue-making?*, (pp.24-26), Copenhagen: IMAE Conference.

Notteboom, T. and Vernimmen, B. (2008). The effect of high fuel costs on linear service configuration in container shipping, *Journal of Transport Geography*, 17(5): 325-337.

Olimb, M., and Ødegard, T. (2010). *Understanding the Factors Behind Crude Oil Price Changes*, Trondheim: Norwegian University of Science and Technology Social Science and Technology Management.

Priog, R. (2005). World oil demand and its effect on oil prices, *CRS Report for Congress*. Congressional Research Service.

Robe, M.A., and Wallen, J. (2016). Fundamentals, Derivatives Market Information and Oil Price Volatility, 36: 317-344.

Sengupta, R., and Tam, Y. (2009). Recent Movements in the Baltic Dry Index, *Economic SYNOPSES*, Federal reserve banks of St. Louis, No:12.

Sevüktekin, M., and Nargeleçekenler, M. (2010). *Ekonometrik Zaman Serileri Analizi*, Ankara: Nobel Yayın Dağıtım

Simons, H. (2011). *Baltic Dry Index No Longer a Valid Economic Indicator*, 14 March 2011, http://www.minyanville.com/businessmarkets/articles/baltic-index-economic-indicator-ocean-freight/3/14/2011/id/33292, (29 March 2019).

Stopford, M. (2009). *Maritime Economics*, New York, NY, USA: Routledge.

Tse, Y. and Tsui, A. (2002) A Multivariate Generalized Autoregressive Conditional Heteroscedasticity Model with Time-Varying Correlations, *Journal of Business and Economic Statistics*, 20(3): 351-362.

Tvedt, J. (2003). A new perspective on price dynamics of the dry bulk market, *Maritime Policy and Management*, 30(3): 221-230.

UNCTAD, *Data Center*, https://unctadstat.unctad.org/wds/ReportFolders/reportFolders .aspx, (10 May 2019)

UNCTAD, *Handbook of Statistics* (2018), New York, USA: United Nations Publication, 72-83.

Wang, Z. (2003). Hedonic prices for crude oil, *Applied Economic Letters* 10: 857-861.

Yıldız, B., and Bucak, U. (2017). Determinants of Freight Rates: A Study on the Baltic Dry Index, *IGU J. Soc. Sci*., 4(2): 17-32.

APPENDICES

APPENDIX 1: Baltic Dry Index Monthly Return Data Between 1988-2018

Return Data for Baltic Dry Index (1988-2018, Monthly) - 1st Difference												
	January	February	March	April	May	June	July	August	September	October	November	December
1988	0,097178399	0,115786947	0,033325938	-0,174559551	-0,00664945	-0,11039748	-0,00914767	0,060772038	-0,0015736	0,07798123	0,0891334	0,027597021
1989	0,048080101	-0,041620131	0,049004779	-0,001226994	-0,02046583	-0,1217854	-0,01425541	0,023413627	-0,0042165	0,14829858	0,0036364	-0,03760073
1990	0,032141209	-0,024631787	-0,04788658	-0,116394203	-0,04662499	-0,17633489	0,067461243	0,036245012	-0,0336732	0,1139706	0,0293585	0,070179111
1991	0,018500014	0,145090264	-0,05677853	0,010510143	0,077484798	-0,03121641	-0,1498538	0,052486307	-0,0136855	0,08246255	-0,040696	-0,0616478
1992	-0,04378264	-0,157185584	-0,03497442	0,030052345	0,041085118	-0,14955719	-0,0288258	0,012189556	-0,0302767	0,06507872	0,1723712	0,03936639
1993	-0,07170177	0,071701771	0,090464984	0,033369141	0,043444037	-0,09697515	-0,09537807	0,068544675	-0,0133382	-0,0717731	-0,049816	-0,0307966
1994	-0,01242252	-0,071675037	0,076662578	0,159113469	0,030643066	-0,08888369	0,076461166	-0,00278164	0,14254359	0,12153337	0,035202	0,014351861
1995	0,004062982	0,032413708	0,08057099	0,060597992	-0,11310715	-0,0574391	0,022978034	0,037319572	-0,0905641	-0,2160076	0,0608147	-0,02463179
1996	-0,0650374	-0,097041551	0,059761735	0,00688234	-0,08514257	-0,11545192	-0,11255782	0,031396854	-0,0953102	0,2707902	0,0819771	0,063307968
1997	-0,10345673	0,054105722	0,047370155	-0,18377668	0,011843802	0,035470179	-0,03077166	0,038318864	-0,0406654	0,03160186	-0,114847	0,0465587
1998	-0,16956814	0,038702329	-0,11155249	0,038583466	-0,05950473	-0,09997219	-0,03688699	-0,00974429	0,14660347	0,00946877	-0,014768	-0,16985968
1999	0,040721234	0,1532866	-0,06647677	0,190235466	-0,10525868	-0,01229524	0,033454716	0,034300276	0,18023203	0,08331725	0	-0,02397119
2000	-0,02397119	0,149047	0,080896486	-0,019465335	-0,03882767	0,031429363	0,015961051	0,006071664	0,05132356	0,01143523	-0,050725	-0,04464208
2001	-0,06125021	0,021704239	-0,06657921	0,01449801	-0,04916721	-0,00216216	-0,27858457	-0,12363904	0,02661147	-0,1004705	0,0080972	0,009174376
2002	0,035878288	0,127040105	0,048281975	-0,052169249	0,014500012	-0,0361544	-0,03751073	0,067890336	0,27725141	0,0359234	0,0961439	0,108049206
2003	-0,12746729	0,142316222	0,094588419	0,099567596	-0,00702744	-0,00094073	0,026011685	0,037791272	0,27870147	0,4199493	-0,030765	0,075836804
2004	0,152680555	-0,053276885	-0,08751243	-0,197449933	-0,18606783	-0,08939345	0,297945364	0,033522692	-0,0195399	0,18150921	0,2065086	-0,27460212
2005	-0,02421426	0,051672011	-0,01901157	-0,185994457	-0,1790024	-0,2444151	-0,33464923	0,362423357	0,11469184	0,06846527	-0,11674	-0,14046616
2006	-0,14553261	0,252968247	-0,07112734	-0,052643733	0,028311633	0,196182358	0,102826945	0,157926972	0,02490181	0,02330641	0,0714504	0,013970226
2007	-0,03990323	0,120278276	0,122876721	0,148087154	-0,04534699	0,050137041	0,104133258	0,100295319	0,20707117	0,11757191	-0,042755	-0,11037907
2008	-0,41259976	0,229468516	0,059658315	0,146502221	0,201098137	-0,17649938	-0,13943349	-0,20293785	-0,749796	-1,3297924	-0,17413	0,079289331
2009	0,323842054	0,618463917	-0,20678761	0,100643526	0,671068729	0,072573555	-0,11466042	-0,32477967	-0,0866735	0,33486219	0,2252683	-0,25736008
2010	-0,05366057	-0,039389267	0,090717673	0,112208264	0,195453009	-0,52764105	-0,20145608	0,321545494	-0,103601	0,09061621	-0,243609	-0,16878801
2011	-0,47101937	0,122289578	0,201324504	-0,187038547	0,153812899	-0,04632698	-0,11143381	0,247527379	0,15951876	0,03416481	-0,062471	-0,06028611
2012	-0,93839751	0,097980408	0,219403232	0,212379185	-0,22422639	0,084118066	-0,11269144	-0,24369897	0,08582528	0,29224086	0,0568335	-0,44060576
2013	0,083667691	-0,00395518	0,184081346	-0,053029908	-0,06461577	0,369814447	-0,09770416	0,063832057	0,57066008	-0,2865178	0,1912576	0,223472986
2014	-0,71849877	0,125163143	0,079431049	-0,367643204	-0,00958984	-0,09424009	-0,1185186	0,418187368	-0,0760547	0,29517976	-0,213908	-0,38826778
2015	-0,25167986	-0,118605742	0,108688306	-0,018441428	-0,00338983	0,306185544	0,346245748	-0,22513492	-0,0033278	-0,2217556	-0,210738	-0,20029025
2016	-0,41070896	0,037155977	0,265399168	0,493899973	-0,13862461	0,075507553	-0,00607905	0,080511641	0,20755146	-0,020786	0,3399667	-0,22543022
2017	-0,18336268	0,071157194	0,412040262	-0,156595197	-0,23356739	0,025858664	0,048737311	0,224411246	0,13564065	0,11548607	0,036133	-0,14427146
2018	-0,1703872	0,034133006	-0,1220918	0,239874837	-0,20723791	0,239522443	0,232199892	-0,1011083	-0,0250093	-0,0330063	-0,190949	0,031977145

APPENDIX 2:Brent Crude Oil Prices Monthly Return Data Between 1988-2018

Return Data for Brent Crude Oil Price (1988-2018, Monthly) - 1st Difference												
	January	February	March	April	May	June	July	August	September	October	November	December
1988	-0,01775195	-0,062828541	-0,06568349	0,119516465	-0,01762428	-0,04836107	-0,04138522	-0,00134228	-0,1219893	-0,0601979	0,047984	0,162019573
1989	0,114657465	-0,016441944	0,101801793	0,083082099	-0,08683244	-0,0529049	-0,00283367	-0,04944304	0,05792007	0,06217924	-0,009564	0,057573585
1990	0,068656794	-0,070170035	-0,07437982	-0,101802115	-0,01577703	-0,07953315	0,128468931	0,458949749	0,25037341	0,03158751	-0,085448	-0,15682536
1991	-0,18182645	-0,18751107	-0,02382298	0,005227403	0,000521241	-0,05461743	0,065501184	0,018892571	0,03625925	0,08011775	-0,050796	-0,13685287
1992	-0,01367262	-0,006075688	-0,02354369	0,070617567	0,049997529	0,061895514	-0,04445176	-0,02501381	0,02649493	-0,0004935	-0,053218	-0,05731153
1993	-0,04222412	0,060252466	0,017177019	-0,006406856	-0,00860683	-0,04757534	-0,05054808	-0,00477898	-0,0421952	0,0367914	-0,088709	-0,10171221
1994	0,039976772	-0,0348914	0,001448226	0,097150349	0,061126601	0,034601327	0,048903807	-0,04117717	-0,0604026	0,03643503	0,0415737	-0,0761237
1995	0,038181978	0,033276986	-0,00586168	0,09204474	-0,01621657	-0,05834521	-0,08811487	0,015649772	0,03658945	-0,0359685	0,0455038	0,061531335
1996	-0,00447178	0,00836825	0,097832249	0,051545152	-0,08744644	-0,03669649	0,058391552	0,046914791	0,09836389	0,06542191	-0,059694	0,043840282
1997	-0,01014379	-0,121347154	-0,08609616	-0,085634195	0,079867469	-0,07872916	0,048844337	0,007555352	-0,0075554	0,07360483	-0,035864	-0,10960064
1998	-0,1231086	-0,076592445	-0,07143264	0,032297212	0,059537121	-0,16219128	-0,0107041	-0,01417281	0,11338866	-0,049165	-0,140077	-0,11710392
1999	0,123424481	-0,07861858	0,197301301	0,200670695	-0,00393185	0,040533049	0,18484045	0,058031548	0,1086193	-0,0242491	0,1108907	0,035568185
2000	0,001569243	0,085245805	-0,01049404	-0,188817693	0,197870806	0,071632979	-0,03830838	0,051641909	0,09289909	-0,068045	0,0500813	-0,23784401
2001	-0,00156006	0,070812708	-0,11551289	0,046260242	0,09828174	-0,01638213	-0,1236801	0,042559614	-0,0023392	-0,2209991	-0,088517	-0,00479873
2002	0,037245323	0,043331716	0,155839869	0,082182578	-0,0148789	-0,05139711	0,066664582	0,034742948	0,06359999	-0,0307497	-0,123518	0,151800226
2003	0,09585555	0,049736599	-0,06818671	-0,202450928	0,033821548	0,066928355	0,025001302	0,052896946	-0,0976213	0,08820948	-0,029474	0,03620614
2004	0,048135008	-0,013518069	0,085957679	-0,001190122	0,111977456	-0,06572812	0,0828812	0,111776311	0,01070525	0,1417728	-0,143858	-0,08492587
2005	0,116884765	0,021558786	0,154904259	-0,023243569	-0,06428155	0,110792805	0,0566881	0,106437821	-0,0168654	-0,0719949	-0,058023	0,028904778
2006	0,102383877	-0,045137532	0,030263208	0,124100988	-0,00685521	-0,01763816	0,071886386	-0,00599049	-0,1671162	-0,0693272	0,0162996	0,06122509
2007	-0,15164595	0,069787389	0,07511263	0,084038927	-0,00415739	0,055561809	0,079512063	-0,08360205	0,08671691	0,06484624	0,1153782	-0,01614522
2008	0,013653208	0,030028436	0,087151733	0,051066522	0,118567138	0,074666216	0,003018415	-0,15873219	-0,1524302	-0,3062636	-0,310955	-0,27223166
2009	0,083752003	-0,002766253	0,071697736	0,075304383	0,132684083	0,180137673	-0,06270374	0,117989925	-0,0693771	0,07295643	0,0520763	-0,02911799
2010	0,022705616	-0,032286689	0,06661264	0,073237729	-0,11045614	-0,01579225	0,010908715	0,01913307	0,01033067	0,06020134	0,0310832	0,069852414
2011	0,053957866	0,07194472	0,100101823	0,072499162	-0,06945078	-0,01013906	0,027211384	-0,05943912	0,02340389	-0,0295012	0,0110749	-0,02652918
2012	0,025806703	0,075159263	0,050014508	-0,046501037	-0,08183973	-0,14800682	0,07547316	0,09953575	-0,0044205	-0,0102419	-0,024008	0,003935031
2013	0,031200553	0,026987359	-0,0675475	-0,059052842	0,003027198	0,003503994	0,047530881	0,030566679	0,0028715	-0,0228395	-0,011897	0,027180809
2014	-0,02412398	0,007188309	-0,01312525	0,002601748	0,016383247	0,020421781	-0,04603457	-0,04953503	-0,0455036	-0,1047999	-0,095836	-0,24239875
2015	-0,26641481	0,195977195	-0,03878019	0,062926917	0,073819912	-0,04142038	-0,0834099	-0,19541969	0,02337051	0,01686662	-0,089812	-0,15245796
2016	-0,21358663	0,047082487	0,17175212	0,084522021	0,116981047	0,031795499	-0,07084507	0,019606311	0,01579948	0,06142007	-0,101732	0,175479513
2017	0,023543584	0,005299236	-0,0616389	0,013859702	-0,03858624	-0,08194862	0,044498643	0,06430644	0,0825689	0,02393216	0,0865621	0,026126762
2018	0,070617567	-0,055966985	0,010659458	0,088235005	0,065352917	-0,03395531	-0,00215256	-0,02343751	0,08405421	0,02676498	-0,224286	-0,1211865