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Dynamic interrelationships in returns and volatilities among shipping freight markets

Avinash Kumar
World Maritime University

WORLD MARITIME UNIVERSITY
Malmö, Sweden

DYNAMIC INTERRELATIONSHIPS IN RETURNS AND VOLATILITIES AMONG SHIPPING FREIGHT MARKETS

By

AVINASH KUMAR
India

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DECLARATION

I certify that all the material in this dissertation that is not my own work has been identified, and that no material is included for which a degree has previously been conferred on me.

The contents of this dissertation reflect my own personal views and are not necessarily endorsed by the University.

(Signature): Avinash Kumar

(Date): 19/09/2016

Supervised by: Ilias Visvikis

World Maritime University, Malmo

Internal Assessor: Shuo Ma

Institution/organization: World Maritime University

External Assessor: Dimitrios Tsouknidis

Institution/organization: Cyprus University of Technology

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ABSTRACT

Title of Dissertation: **Dynamics Interrelationships in returns and volatilities among shipping freight markets**

Degree: **MSc**

This paper explores and analyzes the return lead-lag relationships and volatility transmission among dry bulk, container and tanker shipping freight market after the financial crisis in 2008. However, there are few numbers of studies that investigates such interactions between shipping freight markets, but no studies that also consider potential linkage between container and tanker freight market. This study fills the gap by examining lead-lag and volatility spillover effects among these three shipping freight markets. The Granger causality test and the co-integration analysis are applied to investigate the lead-lag relationship among the Baltic dry index (BDI), Shanghai (export) containerized freight index (SCFI), and the Baltic dirty tanker index (BDTI). Besides, the multivariate Further, the impulse response and variance decomposition method are employed to analyze the response of freight market to the shocks coming from other freight markets. The GARCH-BEKK model is employed to examine transmission effects in freight volatility. On the whole, the empirical results show that there is no lead-lag relationship among shipping freight markets after the financial tsunami in long run. However, these freight markets show positive reaction to own shocks in the short-run. The dry bulk market also respond to shocks coming from the container and tanker freight markets, whereas there is no response in the container market from other two shipping freight markets in the short-run. In addition, the tanker freight market show positive response to impulse coming from dry bulk market but no response to shocks coming from the container freight market. Moreover, there is mutual volatility transmission between dry bulk and container freight markets only. The findings of this study contain useful information about volatility spillovers for maritime players and help them in planning for portfolio diversification, hedging strategies, and forecasting freight rates.

KEYWORDS: Lead-lag relations; Volatility transmission; Cointegration; Impulse; Shipping freight market; GARCH-BEKK; VAR model; VECM models.

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Abbreviations

ADF	Augumented Dicky-Fuller
ARFIMA	Autoregressive Fractional Integrated Moving Average
AIC	Akaike Information Criterion
ARIMA	Autoregressive Integrated Moving Average
ARCH	Autoregressive Conditional Heteroskedasticity
ARMA	Autoregressive Moving Average
BCI	Baltic Capesize Index
BCTI	Baltic Clean Tanker Index
BDI	Baltic Dry Index
BDTI	Baltic Dirty Tanker Index
BHMI	Baltic Handymax Index
BITR-Asia	Baltic International Tanker Routes Asia
BPI	Baltic Panamax Index
BSI	Baltic Supramax Index
CCFI	China (Export) Containerized Freight Index
DCC-GARCH	Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity
DOE	Design of Experiments
ECM	Error Correction Model
J-B	Jacque- Bera
KPSS	Kwiatkowski–Phillips–Schmidt–Shin
MGARCH	Multivariate Generalized Autoregressive Conditional Heteroskedasticity
PP	Phillips-Perron
QMLE	Quasi-Maximum Likelihood Estimate

SBIC	Schwarz's Bayesian Information Criterion
SSE	Shnaghai Shipping Exchange
VAR	Vector Autoregressive
VaR	Value at Risk
VECM	Vector Error Correction Model

1. Introduction

Maritime transport is a major means of transportation for global trade and logistics. Shipping still represents heart and soul of international trade and plays a significant factor in the global economy. Nearly, 90 % of global trade by volume is transported by ships (Review of Maritime Transport, 2009). It is capital intensive industry based on the prevailing price levels, which makes ship-owners or companies to take an account of market volatility in order to run stable business operations. A distinct feature of the maritime industry is that sea transportation and segmentation are facilitated as per the demand of trade per type of cargo throughout the world. In general, the shipping industry is segmented into dry bulk, container and tanker industry. Dry bulk ships are those merchant ships, which are specially designed to transport unpackaged bulk cargoes like, iron ore, grain, coal at the cost of tariffs whereas, tanker vessels are merchant ships specially designed to transport oil or refinery products in bulk to facilitate seaborne trade. Container shipping segments are characterized by transportation of goods in standardized boxes. Dry bulk and tanker market are a nearly perfect competitive industry while container shipping is a monopolistic competitive market. Currently, however, in liner shipping, freight rate mechanism are decided by leading shipping alliances, shipping pools, joint-ventures, consortia and partnership, etc. (Ma, 2015). Hence, Freight rates are stable and transparent in the short run. In contrary, freight rates of dry bulk and tanker markets are determined by demand-supply equilibrium in the market (Stopford, 2009). It means that uncertainty of demand and supply determines freight rate volatility. So, shipping companies are forced to accept the freight rate whatever market forces have decided. These rates are affected by global climate, demand, weather, politics, geographical region, and several others factors. Consequently, that emanates high volatility and fluctuations in freight rates which cause enormous freight rate risk to ship owners and charterers.

1.1 Relations among shipping freight markets

However, despite the pronounced segmentation of shipping freights markets, these markets are not completely isolated from each other (Stopford, 2009). From 2006 to 2007 it was found that some ship-owners converted multipurpose ships that were originally used for transportation of containerized cargo into dry bulk ships to earn more financial revenue in healthy demand of dry bulk commodities (Hsiao, Chou, & Wu, 2013). Moreover, it also increased the demand for containers to transport some bulk commodities. As far as transportation of cargoes carried by bulk ships and container ships is concerned, dry bulk ships mainly transport raw materials, whereas container ships transport finished or semi-finished products. Hence, that causes a lead–lag relationship between these freight markets. To illustrates, when the market is in an upturn, bulk shipping will lead in reflecting the changes of the economic climate. Since the demand of raw material will react first, due to indications of future higher demands of finished or semi-finished products; while market is a downturn, the demand of finished products are firstly influenced while raw materials followed the same trend due to reduction in industrial production.

Likewise, Beenstock and Vergottis (1993a) state that dry bulk and tanker markets cannot drift too far from each other due to existence of multipurpose carriers that operates in both markets, as well as shipbuilding and demolition activities. The fleet of multi-purpose carrier switch from dry bulk to tanker market during strong transportation demand of oil or refinery products compare to dry bulk cargoes. Consequently, this switching scenario increases supply in the short run until subsequent deliveries and growth of new building activity restore the demand-supply equilibrium (Taylor, 2014). Following this reasoning in line, freight markets of both maritime sectors significantly affect each other in the short-run, which shows an integrated relationship and volatility transmission between these two freight markets.

Similarly, the tanker and container markets have a significant relationship to each other. Seaborne demand is greatly influenced by world economy and global trade (Jugovic, Komadina, & Hadzic, 2015). Consequently, global economy creates demand of raw materials and energy (oil) for industrial production of finished or semi-finished products, which significantly affect the demand and supply of the tanker and container market in the maritime industry. Besides, industrial productions are somehow also dependent upon the energy commodity market to run the factories or industry to produce final product, which clearly state that containerized cargoes are also affected by the energy (oil) market and related tanker shipping market to some extent.

This is due to fact that different sector of shipping industry has intrrelations to each other despite of notable segmentation.

1.2 Research questions

This dissertation aims to research the lead-lag relationships and volatility transmission among dry bulk, container, and tanker freight markets. Therefore, this dissertation contributes to literature in the following ways:

Firstly, this study examines the lead-lag relationship of returns among dry bulk freight, container, and tanker freight markets by using financial tools. The lead-lag relationship between shipping freight markets illustrates how one shipping freight market respond to new economic climate change compare to another freight market, and how well the two markets are interrelated to each other. The casual relationships among freight markets are estimated by using a co-integration test, the Engle-Granger casualty test and the Vector Error Correction Model (VECM) depending upon characteristics of time-series data of shipping freights.

Secondly, the financial crisis in 2008 predominantly affected the maritime industry. It emerged as a negative shock, which caused abrupt fluctuations in different shipping freight markets. As this study consider quantitative methods to examine fluctuations of one shipping freight market in the current period due to the persistence of previous own shock and/or other shipping freight markets. Impulse response and variance decomposition method in the Vector Auto-regression (VAR) and VECM model are used to analyze the response of the freight market due to existence of shocks.

Thirdly, this study investigates in detail volatilities spillovers effects and transmission effects among shipping freight markets. Recently, rapid economic growth of emerging countries has apparently led to volatility for shipping freight markets. Kavussanos and Visvikis (2006) suggested that shipping freight market is significantly influenced by great volatility and an enormous level of risk. Furthermore, Stopford (2009) investigated that volatility of dry bulk, container, and tanker freight markets are different in the short run, while in the long-run, fluctuations in freight market of a shipping segment would affect the freights of another segment; since they are part of the same industry. Therefore, Multivariate Generalized Auto-regressive Conditionality Heteroskedasticity (MGARCH) models are employed in this study to explore volatility spillovers effect between different shipping freight markets. At the empirical stage, Baba, Engle, Kraft and Kroner (BEKK) model of Engle and Kroner (1995) is employed to analyze the characteristics of conditional covariance equation to reflect the volatility transmission among different freight markets while mean spillovers are captured by a VAR and/or VECM representation.

1.3 Research contributions

The contribution of this literature can be unfolded from following aspects:

Firstly, being a capital intensive industry, freight volatility causes a high level of threat in maritime business and profitability. So, several shipping players in shipping and financial markets (ship-owners, charterers, ship-lending financial institutions, investors, and regulators) can grasp a better understanding of return the lead-lag relationship and volatility transmission among dry bulk, container, and tanker freight markets (Tsouknidis, 2016). Thus, it would put them in healthy decision making process of portfolio diversifications, hedging and managing freight rate risks and forecasting shipping freights rates.

Secondly, the volatility interactions among three related freight markets can provide an effective risk prediction mechanism, which can enhance the decision-making process among shipping players. Further, it increases efficiency in estimating cost of shipping freight derivatives (Tsouknidis, 2016).

Thirdly, there is clear evidence during crisis events that the volatility expands strongly and spills over to another market which demonstrates co-movements of markets (Reinhart & Rogoff, 2008). Thus, investigating and measuring volatility transmission can define early signs of shipping freight market crisis and the effective application of hedging risk strategies by investors and regulatory authorities.

Fourthly, in general, maritime freight rate assumes a real part of money stream generating capability of shipping companies, charterers, individual investors and financial institutions. It stems the fact that shipping freight markets expose excess volatility along with a number of other distinct features. Shipping freights rates significantly affect the global capital markets and furnish an effective global economic action pointer (Alizadeh & Muradoglu, 2014). So, it is extremely important for all players in the maritime business and capital markets to investigate volatility spillovers across shipping freight markets.

1.4 Research structure

This research paper is divided into six chapters:

Chapter one is sub-divided into four parts. First, it describes the interrelationship and co-movement of freight markets. Second, objectives of the research paper are discussed in detail. Third, this sub-chapter describes about research contributions of this study and its importance to various market practitioners. Lastly, it proposes the structure of the study.

Chapter two contains brief history and research development on the volatility of freight markets. It contains literature review on volatility transmission and lead-lag relationship among dry bulk, container and tanker freight markets. It also overviews all findings related to the relation among freight markets. Finally, it states about the gap in research studies which has to be covered in this thesis.

Chapter three discusses research background of the literature and data analysis. It describes freight indices and selection of index for quantitative analysis in this literature. Furthermore, it also shows the trend and financial characteristics of selected time-series freight indices in data analysis.

Chapter four describe all the theories related to the empirical model employed in this study. It explains the concept and importance of the applied quantitative model in the investigation of lead-lag relations and volatility transmission across shipping freight markets. It also explains the concept about stationarity of data in level or in first differences through different unit root test, the optimal lag selection test and the long run co-integrating relationship between shipping freight markets. Moreover, it gives a clear theory and concept of VAR and VECM model related to objective findings. In the last section, the theories of MGARCH model are discussed.

Chapter five is mainly focused on application and results of the empirical model employed in this study. It states clear quantitative evidence about interrelations and the volatility transmission effect in shipping freight markets. It also includes discussion and economic justification of empirical results found in this literature.

The last chapter of this literature is about the conclusion. It provides an outlined summary of aims and objectives of the study. The main outcomes of this research are also referred to this chapter. It also focuses on the difficulties and limitations of the research work performed. In addition, this chapter also mentions the scope available for further research work in this research topic. The thesis is concluded by suggesting some information that should be considered by the shipping players to make shipping business to increase.

2. Literature Review

In this research, the volatility spillover and lead-lag relationship relation among maritime shipping freight market are analyzed by employing Generalized Auto regressive conditional Heteroskedasticity- Baba, Engle Kraft and Kroner (GARCH-BEKK) and Johansen co-integration test. So, the related literature exists in four strands. First, studies on volatility and spillover effects, especially in econometrics, will be reviewed briefly. Second, applications of the econometric time series model to dry bulk market will be considered. Thirdly, research on tanker freight markets will be examined. Fourth, studies conducted on container freight market will be considered.

2.1 Spillover effect and volatility

In the existing literature, many studies have been conducted to find the linkage and spillover effect between shipping freight markets. Hsiao, Chou and Wu (2013) investigate the lead-lag relationship and volatility conveyance between the dry bulk and container freight markets by using the Johansen co-integration analysis and the Granger causality test followed by GARCH-BEKK model. The empirical results showed that the Baltic Dry index (BDI) and the China (export) Containerized Freight Index (CCFI) stand in long-run equilibrium relationships. In the case of volatility transmission between these shipping sector, they found that BDI has significant, long-run continuous effect on CCFI, whereas CCFI has a short-run spillover effect on the BDI.

Likewise, Tsouknidis (2016) investigated the existence of dynamic volatility spillovers within and between dry bulk and tanker freight markets by adopting the multivariate dynamic conditional correlation GARCH (DCC-GARCH) and volatility spill over index developed by Diebold and Yilmaz (2012, 2009). He concludes that there is severe existence of pronounced volatility spillovers effects among these two markets during financial crisis. This study also reveals that large volatility spillovers exist between dry-bulk and tanker sub-segments for a short period of time[1]. He also suggests smaller vessels have transmission effect of volatility spillovers to larger vessels within dry-bulk segments.

A similar study, Kavussanos, Visvikis, and Dimitrakopoulos (2014) investigate the spill over relationship among the dry bulk shipping derivative market and the corresponding derivative market for commodities. In order to determine the order of integration of each price, they employed the standard unit root tests of Dickey and Fuller (ADF, 1981), Phillips and Perron (PP, 1988) and Kwiatkowski et al. (KPSS, 1992). Lastly, they used the final test of Lee and Strazicich (2003, 2004) (LS henceforth) that accounts for structural breaks in series. For a given set of two non-stationary series, Johansen test was used to determine the long run relationship between them; that is, they are co-integrated and estimated by VECM model. Consequently, the empirical results show that the commodity derivative market; by using GARCH-BEKK(1988), lead return and volatility compare to dry bulk shipping derivative market.

Moreover, Kavussanos and Visvikis (2003) had conducted research on the lead –lag relationship between dry bulk spot market and forward markets. They employ the Quasi-Maximum Likelihood Estimates (QMLE) estimation method for VECM-GARCH model for Route 1(US-Gulf to ARA) and the VECM-GARCH models for Routes 1A, 2, and 2A, on the basis of LR tests, Schwartz information criteria, and diagnostic tests.

Dai, Hu, and Zhang (2015) proposed the multivariate GARCH-BEKK model to capture the volatility transmission effect from freight markets, newbuilding, and secondhand vessels markets in the global dry bulk shipping market. According to their empirical results, it was proved that there is the existence of significant bilateral and unidirectional interactions among freight market, new building price, and secondhand price (Dai, Hu, & Zhang, 2015, p. 360). Chen, Meersman, and Voorde (2010) critically analyzed the dynamic interrelationships in returns and volatilities between Capesize and Panamax market in four major trading routes, the transatlantic, the fronthaul, the transpacific, and

[1] Segments and sub- segments of dry-bulk and tanker ships refer to division of particular sector according to size of fleet like handymax, aframax, ULCC, VLCC etc.

the backhaul. They considered the sample period from 1999 to 2008, which split into two sub-periods due to substantially different economic conditions and market characteristics over these periods[2]. In order to examine long-run equilibrium relationships between price series, they employed the Johansen (1988, 1991) co-integration test and the Granger causality test to identify whether two variables move one after the other or if they move contemporaneously. The volatility spillovers between these markets were investigated by using an extended bivariate Error Correction Model GARCH (ECM-GARCH) model. Consequently, the results showed that there are bidirectional volatility spillovers between both markets in transatlantic route and, whereas unidirectional spillover effects were found in both the fronthaul and the transpacific routes. Consequently, the Panamax market leads the Capesize market in the transatlantic route and lags in the transpacific routes. In the backhaul route, the coefficients of the volatility spillovers in either market are not significant at the conventional levels, indicating that there are no volatility spillovers in any direction at these significance levels.

2.2 Dry bulk shipping freight market

Based on monthly data from January 1992 to May 2012, Ko (2013) applied the VAR model and two-time varying cointegration model to analyze term structure in bulk shipping. Overall, three empirical results were concluded as follows: 1) the response of short-term rate to long-term structural shock is large and statistically significant, but not vice-versa . 2) The effect of implied time charter rate becomes larger in the case of more backwardation.3) There is a lack of evidence in stable adjustments speed in both equations for short- and long-term freight rates. Ko (2011) suggested an alternative method of calculating a new index instead of BDI, by using a common stochastic trend model. The empirical results show that the dynamics of smaller ships perfectly capture the dynamic properties of the common stochastic trend. It was also stated that this econometric method explains whether a current sub-market is near the long-run

[2] Different economic condition and market characteristics refers to several factors, which affect demand-supply equilibrium in shipping industry like financial crisis in 2008, strikes, war , and other political issues.

equilibrium or far from it (Ko, 2011, pp. 387-404).Ko (2010) analyzed the term structure of time-charter rates for the dry bulk market on time-dependent volatility. The empirical results show that there is bimodality in shipping supply curve, which means that increment in backwardation leads to more volatility in spot and time charter rates[3]. Consequently, that affects the index of the dry bulk market too.

2.3 Tanker freight market

For the tanker freight market, several studies have been conducted like dry bulk shipping. Beenstock and Vergottis (1989) applied the three stages least square method (3-LS) to estimate an aggregated econometric model in which, inter alia, freight rates, lay-up, new and secondhand prices and the size of the fleet are jointly and dynamically determined. The empirical result suggests that the tanker markets and dry cargo markets are interrelated and their developments spillover to each other. Abouarghoub (2013) measured the uncertainty in tanker freight rate by using univariate and multivariate Value-at-risk (VAR) model which are structured on state-dependent conditional variance model. The result argues that the semi-parametric based VAR model calculates more accurately short-term freight risk than parametric and non-parametric models. Furthermore, tanker freight clusters have a low tendency to shift from a lower volatility state to a higher volatility state, whereas it is more prone to shift from higher to lower volatility state. He also concluded that VAR model is more commonly used for finding interrelationship between the tanker freight market and underlying transported commodity. Kavussanos (2003) estimated the time varying volatilities among operating tanker vessels of different sizes in spot and time charter rates. Co-integration error correction Autoregressive Conditional Heteroskedasticity (ARCH) models are used to investigate time varying volatility transmission between spot and time charter rates. Overall, it was concluded that the spot rates are more volatile than time charter rates and freight of larger vessels having higher volatilities compared to freight of smaller vessels.

2.4 Container freight market

Likewise, there are several studies conducted on the container freight market. Luo, Fan, and Liu (2009) employ a three-stage least square method to present an econometric analysis of fluctuation of freight rates due to the interaction between demand of liner ships and the container fleet capacity. The model parameters were estimated by annual container shipping market data from 1980 to 2008 from Drewry and Clarksons. The empirical results can explain 90% of variations in fleet capacity and freight rate, as models are stable and provide high goodness of fit[3]. They estimated that freight rate would be decreased in the coming next three years if the demand of container transportation grows less than 8%.Furthermore, Rasmussen (2010) employed Auto-regressive Moving Average (ARMA) and Autoregressive Fractionally Integrated Moving Average (ARFIMA) models to forecast the container freight rates for the three major shipping routes. It was further investigated that how container freight rates are r affected by different variables, such as time charter rates and bunker oil prices, by using a vector autoregressive model. A similar study by Nielsen et.al (2014) estimated the forecast of the container freight market by exploring the relationship between individual company's rates and market's force determined rate, thus assisting in dealing with market volatility for given business situation. To arrive to this model, the Autoregressive Integrated Moving Average (ARIMA) was employed on time-series weekly SCFI data from 2010 to 2012. To further investigate the behavior of estimated model robustness, performance, limitation, a Design of Experiments (DOE) model was employed. Fan and Yin (2015) analyzed the dynamic interrelationship among different prices in the container shipping market such as new building prices, time charter rate, and second hand prices. To test the long run relationship the co-integration test of Johansen' VAR approach was adopted. As a result, failure of co-integration indicates structural changes in variables, which was tested by Granger causalities test. Finally, the empirical results show that the time charter rate is more active in an increasing market trend.

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[3]. Estimated result of R- square represents goodness of fit of model.

2.5 Summary

However, a great deal of research on volatility transmission across different assets or markets has been done in other financial sectors due to their important roles in portfolio risk management and market stability assessment (Dai, Hu, & Zhang, 2015, p. 354). The above literature reviews suggest that the study on the lead-lag relationship and volatility transmission among bulk, container, and tanker freight market have not reached consistent conclusions. Besides, to the best of our knowledge, there have not been any studies conducted to find the interrelationship and volatility among these three major freight markets of shipping industry simultaneously. Therefore, this study considers a more in-depth study to explore this impressive topic.

3. Research background and sample data

3.1 Research background

3.1.1 The Baltic Exchange dry bulk index

Global dry bulk shipping plays a crucial role in the proliferation of global economy and trade (Dai, Hu, & Zhang, 2015, p. 353). The past decade has witnessed great fluctuations in dry bulk shipping market, which is reflected by the abruptly change in BDI. The BDI, established on 1 November 1999, was calculated by taking an average of three standard shipping market freight indices: the Baltic Capesize Index (BCI), the Baltic Panamax Index (BPI), the Baltic Supramax Index (BSI) and the Baltic Handymax Index (BHMI) (the Baltic Exchange, 2016,). Later on,from 2 January 2007, BDI has been calculated as weighted average of four standard shipping freight indices: the BCI, the BPI, the BSI, and the BHI (Hsiao, Chou, & Wu, 2013, p. 701).

The BFI experienced several modifications since its birth, with the addition of new routes such as South America to the Far East, while less popular routes were withdrawn. Following these alteration and increasing segmentation in the global dry cargo shipping industry, several sectorial indices were continuously announced over time by the Baltic Exchange, such as the Baltic Panamax Index (BPI) launched in 1998; the Baltic Capesize Index (BCI) in 1999; the Baltic Handymax Index (BHMI) created in 2000 and the Baltic Supramax Index (BSI) in 2005 (Geman & Smith, 2012).

Table 1 Dry bulk indices and related route and panel members

Index	**Routes**	**Publishing times**	**Frequency**	**Panel Members**
Baltic Exchange Dry Index (BDI)	Time charter elements of the Baltic Capesize, Panamax, Supramax & Handysize Indices	1300 (London)	Monday to Friday	See below
Capesize (BCI)	Tubarao to Rotterdam Tubarao to Qingdao Richards Bay to Rotterdam W Australia to Qingdao Bolivar to Rotterdam Gibraltar-Hamburg Transatlantic Round Voyage Continent/Mediterranean trip Far East Pacific Round Voyage China/Japan trip Mediterranean/Continent China-Brazil round voyage Richards Bay to Fangcheng Revised backhaul	1300 (London)	Monday to Friday	Arrow Chartering (UK) Banchero-Costa Barry Rogliano Salles Clarksons Platou Fearnleys EA Gibson Shipbrokers Howe Robinson Partners Ifchor I & S Shipping LSS Geneva Simpson Spence Young Thurlestone Shipping
Panamax (BPI)	Transatlantic RV Skaw-Gibraltar/Far East Japan-South Korea/Pacific Round Voyage Implied voyage Newcastle-Qingdao Far East/NoPac-Australia/Skaw-Passero	1300 (London)	Monday to Friday	Acropolis Chartering Arrow Chartering (UK) Banchero-Costa Chinica Shipbrokers Clarksons Platou Fearnleys EA Gibson Shipbrokers Hai Young Howe Robinson Partners

				Ifchor LSS Geneva Optima Chartering Simpson Spence Young Thurlestone Shipping Yamamizu Shipping Co
Supramax (BSI)	Antwerp-Skaw trip Far East Canakkale trip Far East Japan-South Korea/NoPac or Australia Round Voyage Japan-South Korea trip Gibraltar-Skaw range US Gulf-Skaw-Passero Skaw-Passero-US Gulf West Africa via east coast South America to North China West Africa via east coast South America-Skaw-Passero	1300 (London)	Monday to Friday	Arrow Chartering (UK) Ausea Beijing Clarksons Platou Hartland Shipping Ifchor Howe Robinson Partners John F Dillon & Co Lightship Chartering Rigel Shipping Simpson Spence Young Yamamizu Shipping Co
Panamax (BEP Asia)	South China, one Indonesian round voyage	1300 (Singapore)	Monday to Friday	Arrow Chartering (Singapore) Chinca Shipbrokers Clarksons Platou Asia Pte Limited Howe Robinson Partners (Singapore) Ifchor (Hong Kong) Interocean Simpson Spence Young (Asia) Thurlestone Shipping (Singapore) Yamamizu Shipping Co

Supramax (BES Asia)	East coast India - China South China via Indonesia / east coast India North China via Indonesia / South China	1300 (Singapore)	Monday to Friday	Ausea Beijing Braemar ACM Shipbroking Clarksons Platou Asia Pte Limited Galbraith's Shanghai Howe Robinson Partners I & S Shipping Interocean Delhi Simpson Spence Young (Asia) Yamamizu Shipping Co
Handysize (BHSI)	Skaw-Passero trip Recalada-Rio de Janeiro Skaw-Passero trip Boston-Galveston Recalada-Rio de Janeiro trip Skaw-Passero US Gulf trip via US Gulf or north coast South America to Skaw-Passero South East Asia trip via Australia to Singapore-Japan South Korea-Japan via NoPac to Singapore-Japan	1300 (Singapore)	Monday to Friday	Ausea Beijing Barry Rogliano Salles Braemar ACM Shipbroking Clarksons Platou Shipbroking (Switzerland) SA Clarksons Platou Asia Pte Limited Doric Shipbrokers Hartland Shipping Howe Robinson Partners H Vogemann Ifchor Lightship Chartering Rigel Shipping Simpson Spence Young Simpson Spence Young (Asia) Yamamizu Shipping Co

Source: The Baltic exchange

Every business day, a panel of international shipbrokers provides freight information about several routes to the Baltic exchange (The Baltic Exchange, 1985). These freight rates evaluations are then weighted together to calculate both overall BDI and fleet size specific indices like BCI, BPI, BSI, and BHI.

Table 2- Composition of BDI

Ship Classification	**Dead Weight Tons**	**% of World Fleet**	**% of Dry Bulk Traffic** []
Capesize	172,000	10%	25%
Panamax	74,000	19%	25%
Supramax	52,454	37%	25% w/ Handysize
Handysize	28,000	34%	25% w/ Supramax

Source: Wikinvest, "Composition of the Baltic Dry Index"

The following mathematical specification is used to calculate the BDI:

(avg CapesizeTC + avg PanamaxTC+ avg SupramaxTC + avg HandysizeTC)/ 4) * 0.110345333
where, avg = average, and TC = Time Charter (The Baltic Exchange, 1985).

With the expeditious rise in the economy of China and other developing countries, the BDI has undergone significant fluctuations since 2003.Due to flourishing international trade and the global economy in 2006-2007, the BDI boost up more than 10000 points (Hsiao, Chou, & Wu, 2013). However, in 2008, the financial crisis had great turmoil in the maritime industry, which contributed to sharp decrease of the BDI (starting in June) and the CCFI (starting in August) (Hsiao, Chou, & Wu, 2013).

In order to soothe the sway of the financial tsunami, the global community encouraged expansions of domestic demands by relaxing monetary policy and invigorating domestic utilization and investments to stimulate industrial production, infrastructure , real state, and global trade growth (Hsiao, Chou, and Wu, 2013). By the middle of 2009, there was gradually rise in demand for raw materials and commodities through seaborne trade. However, in 2010, crushing housing policy in china coupled with european debt problem and expanding fleet capacities, the BDI fell sharply in the second half (Hsiao, Chou, and Wu, 2013). As tramp shipping is a near-perfect competitive market, the freight mechanism is determined by supply and demand in the market. Henceforth, this study considers BDI as a proxy of indices for dry bulk shipping.

Trends of BDI from January 2000 to June 2011

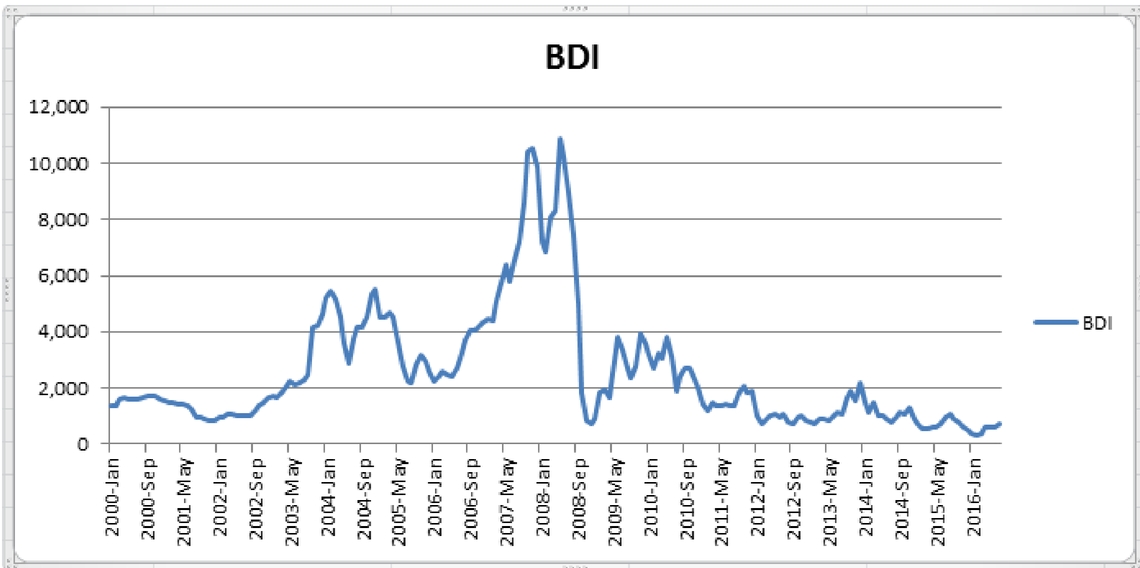

Figure1

Source: Clarksons Shipping Intelligence Network

3.1.2 The Baltic Exchange tanker index

Similar to the dry bulk market; tanker freight market is also a nearly perfect competitive market. Freight rate is decided by market force according to the interplay of demand and supply of tanker shipping services. The demands of tanker market depend on imports and exports of oil, world economic activity, and economics of other related energy commodities (Stopford, 2009, p.212) .However, tanker market is divided between 'clean tanker' and 'dirty tanker' markets (Stopford, 2009, p. 215). The clean tankers refer to product tankers carrying clean oil products like gasoline, kerosene, and other petroleum fuel, while the dirty tankers refer to crude oil or black oil products. To reflect the changes in tanker freight rates, the Baltic Exchange has established the tanker indices: the Baltic Dirty Tanker Index (BDTI) and the Baltic Clean Tanker Index (BCTI). The Baltic international tanker routes report freight information about 19 international routes, which is compiled to publish BDTI and BCTI from Monday to Friday of each week at 1600 hrs in London (The Baltic Exchange,.2001)

Table 3 Tanker indices and related trade routes and panel members

Index	Routes	Publishing Times	Frequency	Panel Members
Dirty Tanker (BDTI)	280,000mt Middle East Gulf to US Gulf 270,000mt Middle East Gulf to Singapore 265,000mt Middle East Gulf to Japan 135,000mt Black Sea to Mediterranean 80,000mt North Sea to Continent 80,000mt Kuwait-Singapore (Crude/DPP Heat 135F) 70,000mt Caribbean to US Gulf 55,000mt ARA to US Gulf 80,000mt South East Asia to east coast Australia 260,000mt West Africa to China 100,000mt Baltic to UK-Continent 30,000mt Baltic to UK-Continent 80,000mt Cross Mediterranean 130,000mt West Africa to Continent 50,000mt Caribbean to US Gulf		Monday to Friday	Barry Rogliano Salles Bassoe (PF) Braemar ACM Shipbroking Bravo Tankers Charles R Weber Clarksons Platou Clarksons Platou Asia Pte Limited Clarksons (Houston) Eastport Chartering Fearnleys Galbraith's E A Gibson Shipbrokers Howe Robinson Partners Howe Robinson Partners (Singapore) Mallory Jones Lynch Flynn McQuilling Brokerage Partners (New York) McQuilling Brokerage Partners (Singapore) Odin Marine (Singapore) Simpson Spence Young Simpson Spence Young (NY) Simpson Spence Young (Singapore) True North Chartering

Clean Tanker (BCTI)	75,000mt Middle East Gulf - Japan 37,000mt Continent to US Atlantic coast 55,000mt Middle East to Japan 30,000mt Algeria to Euromed 30,000mt CPP/UNL m/distillate Baltic to UK/Continent 65,000mt CPP/UNL m/distillate Middle East Gulf to UK/Continent 38,000mt US Gulf to Continent 80,000mt Mediterranean to Far East 60,000mt Amsterdam to offshore Lome	1600 (London)	Monday to Friday	Barry Rogliano Salles Braemar ACM Shipbroking Bravo Tankers Charles R Weber Clarksons Platou Clarksons Platou Shipbroking (Switzerland) SA Fearnleys Galbraith's EA Gibson Shipbrokers Howe Robinson Partners Howe Robinson Partners (Singapore) McQuilling Brokerage Partners (New York) McQuilling Brokerage Partners (Singapore) Odin Marine (Singapore) Poten & Partners (New York) Simpson Spence Young SSY Tankers (New York) True North Chartering

Source: The Baltic Exchange

With the rapid growth of so-called ‘China growth’ and other emerging economies, tanker freight market has also experienced significant fluctuation since 2003. In 2004, tanker indices boosted up to the highest point for decades by touching the figure of 3050 for BDTI and 1760 for BCTI, due to the Organizations of Petroleum Exporting Countries (OPEC) decisions to boost production levels, increased in demand from major consumer companies and China, and buyer’s decision in uncertain[4] supply environment (Review of Maritime Transport, 2005) .The global financial tsunami impact had started

[4].The uncertainty resulted from the tax issues of a major Russian oil producer, abrupt fluctuations of Iraqi exports and concerns about the outcome of a referendum in Venezuela.

affect demands of the tanker market from the middle of 2008. Consequently, 2009 was a bleak year for the tanker freight market, which fell sharply to the lowest point of the decade in March 2009 i.e. 455 points for the BCTI and 513 points for the BDTI. This was largely attributable to cut in oil production by the OPEC (Review of Maritime Transport, 2009). Figure 2 illustrates that the BDTI and the BCTI showed rollercoaster ride, which had been fluctuating sharply within a short interval of time.

Trends of Baltic dirty tanker and clean tanker index

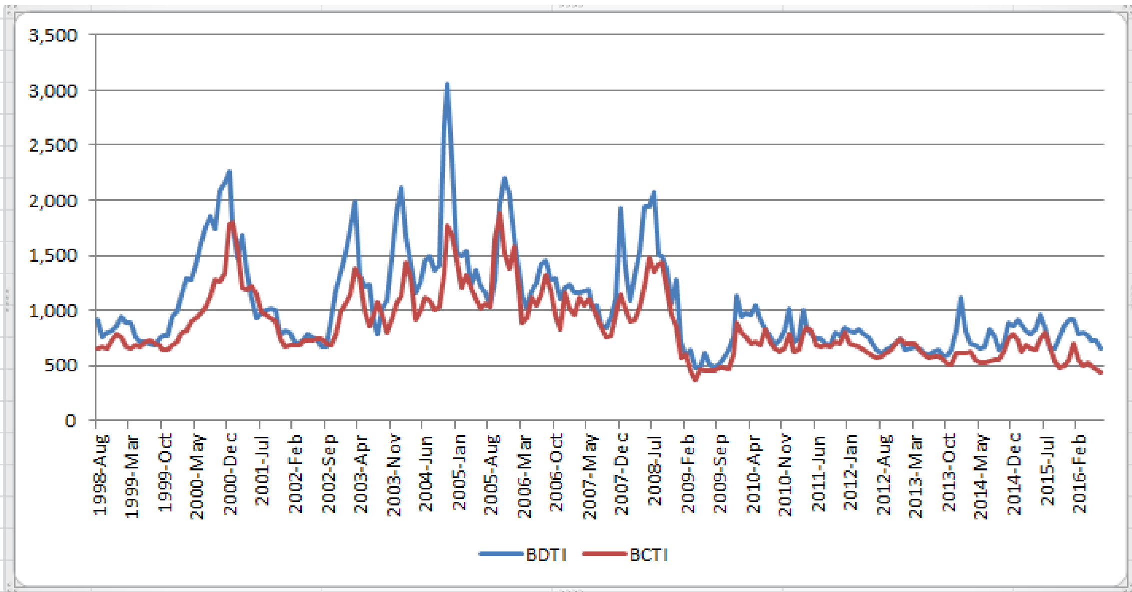

Figure 2

Source: Clarksons Shipping Intelligence Network

Crude oil has an extensive impact on world economy and seaborne trade. As the refined petroleum products are formed through a distillation process of crude oil, which explained the fact that both dirty and clean tanker markets follow same trend of demand in the global market (Tsouknidis, 2016). Specifically, it is well estimated that tanker market derives from international trade of crude oil (Shi, Yang, & Li, 2013, p. 312).Moreover; Alizadeh and Talley (2011) also argue that BDTI reflects the tanker market condition as well as macroeconomics elements of tanker freight rates. Hence, this study considers BDTI as a proxy of tanker indices to represent tanker freight market, which is limited to the dirty oil tanker market only.

3.1.3 Container freight index

Compared to the Baltic indices for bulk and tanker markets, there was no globally recognized freight rate index for the container shipping industry. To accommodate the demand of the agile growing Chinese container market, Shanghai Shipping Exchange (SSE) had published the first container freight index, CCFI on 13th April 1998 (Hsiao, Chou, & Wu, 2013). The main function of the CCFI is to reflect the changes in international container freights with the sole purpose of meeting the fast growing demand of container transportation in the Chinese market. Furthermore, for the purpose of meeting the demand of the derivative market for liner shipping and optimizing the CCFI system, SSE renovated and published Shanghai (Export) Containerized Freight Index (SCFI), which is officially announced on October 16th, 2009 to replace the original SCFI issued on December 7th, 2005 (Shanghai Shipping Exchange, 2009). It reflects the spot rates of 15 individual shipping routes and a composite index, which is published on each Friday and adjusted in legal holidays. A total of 14 container trade routes from Shanghai were selected with the destinations including: Europe, the Mediterranean Sea, US west coast, US east coast, Persian Gulf, Australia/New Zealand, West Africa, South Africa, South America, West Japan, East Japan, Southeast Asia, Korea, Taiwan and Hong Kong. The freight information is provided by world-renowned member panelists for SCFI compilations (Shanghai Shipping Exchange, 2009). At present, 22 liner companies and 17 shippers/freight forwarders report freight rates per week (Shanghai Shipping Exchange, 2009).

Table 4. Name of panelist and shipping companies for container freight indices

Name of Panelist For SCFI	
Liner shipping companies	Shippers/ Freight forwarders
CMA-CGM, COSCO, CSCL, EMC, HANJIN, HASCO, HLAG, HSDG, JINJIANG, K-LINE, KMTC, MAERSK, MOL, MSC, NYK, OOCL, PIL, RCL, SINOTRANS, SITC, WANHAI and YANGMING.	COSCO Logistics (Shanghai), JHJ International Transportation Co., Ltd., Orient International Logistics (Holding) Co., Ltd., Shanghai Asian Development Int'l Trans Pu Dong Co., Ltd., Shanghai BA-SHI YUEXIN logistics Development Co., Ltd., Shanghai Huaxing International Container Freight Transportation Co., Ltd., Shanghai Jinchang Logistics Co., Ltd., Shanghai Orient Express International Logistics Co., Ltd., Shanghai Richhood International Logistics Co., Ltd., Shanghai Sijin International Transportation Co., Ltd., Shanghai Syntrans International Logistics Co., Ltd., Shanghai Viewtrans Co., Ltd., Shangtex Group International Logistics Co., Ltd. (formerly named Shanghai Shenda International Transportation Co., Ltd.), SIPG Logistics Co., Ltd., Sinotrans Eastern Co., Ltd., Sunshine-Quick Group and UBI Logistics (China) Ltd.

Source: The Shanghai Shipping Exchange

The freight rate of each shipping route is the average mean of all freight rates of each route. The minimum number of reports per route per week is subject to the weighting[5] on the specific route (The Shanghai shipping exchange, 2009).

$$P_i = \sum_{j=1}^{n} P_{ij} / n$$

Where: i = shipping route, j = sample company, n = number of sample companies on the route

Furthermore, the composite index is calculated by weighted average of all routes. The average spot freight rate of the specific route is divided by the average price of its base period. The result multiplies its weighting and its base period index to obtain a value of

[5] No less than five reports are required for the shipping route with less than 5% weighting; at least six reports are required for the route of 5%-10% weighting; at least seven reports are required for 10%-15% weighting; and minimum eight reports are required for the route with more than 15% weighting.

each route (The Shanghai shipping exchange, 2009). All the route values shall then add up to obtain the total value.

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

Where: i = route, m = number of the route, W_i = weighting of route i

However, with the rapid development of containerization, the container freight rate begins to fluctuate in a broader range due to the influence of several factors such as decline in dominating power of liner conferences in the liner shipping market and fierce competition. Therefore, it is important to compile a freight index reflecting the volatility of freight rate so as to reveal the economical characteristics of the liner shipping markets (Xin, 2000). So, the Chinese government wants a simple freight index as easy to read and understand benchmark for buyer and seller, which reflects changes in demand and supply by communicating health of the market. Consequently, the SCFI provides a platform for liner shipping players to offsets risks in the derivative market and gain knowledge about spot rates more efficiently. Thus, this study has considered SCFI as the proxy of container freight rate for further estimation.

Trends of fluctuation in container freight indices from October 2009 to April 2016

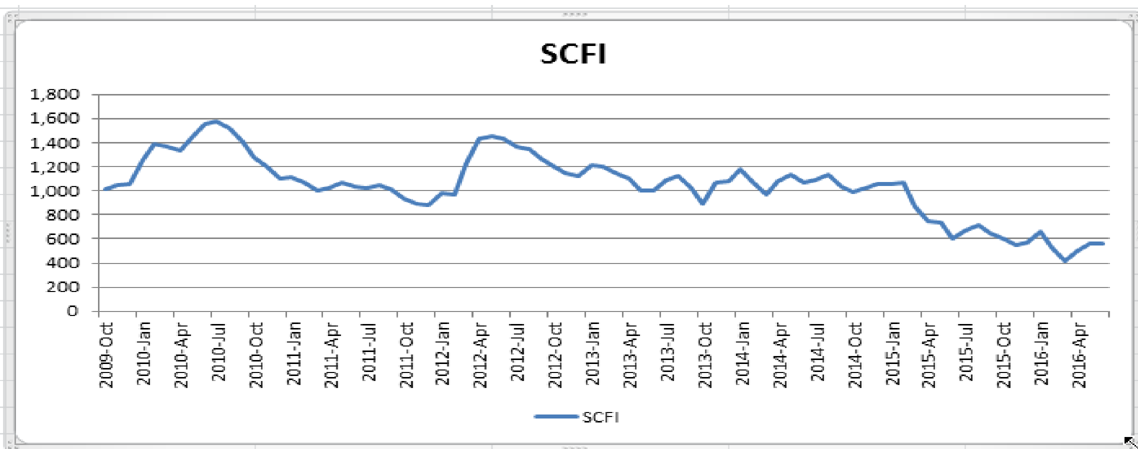

Figure 3

Source: Clarksons Shipping Intelligence Network

Figure 3 illustrates fluctuation of SCFI from October 2009 to April 2016. As seen in above graph, the SCFI hit a record of the highest 1573 points in July 2010, while the lowest point (414points) in March 2016. The highest SCFI in 2010 is attributable to several factors: practices adopted by the operators to absorbed tonnage supply (for example, some vessels by laying up of some vessels and added other vessels to existing routes with slow steaming); a fall in fuel prices, in some cases by as much as 30 percent; and most importantly, an increase in demand from merchandise trade (Review of maritime transport, 2011).

3.1.4 Trends of Logarithmic return rates of BDI, SCFI, and BDTI.

Trends of Logarithmic return of BDI

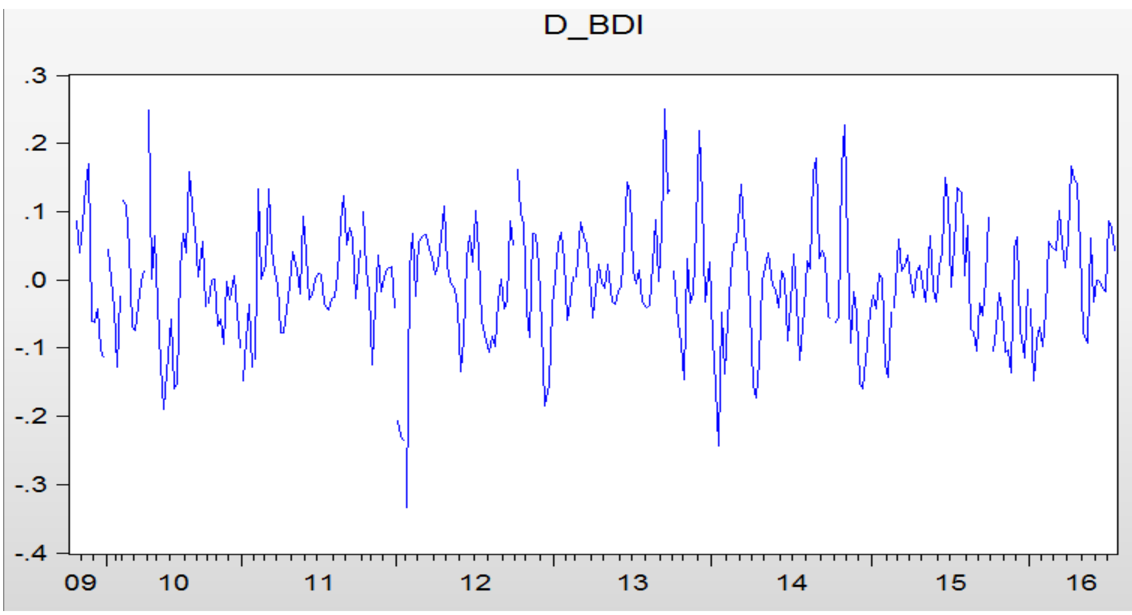

Figure 4

Logarithmic return rates trend of SCFI index

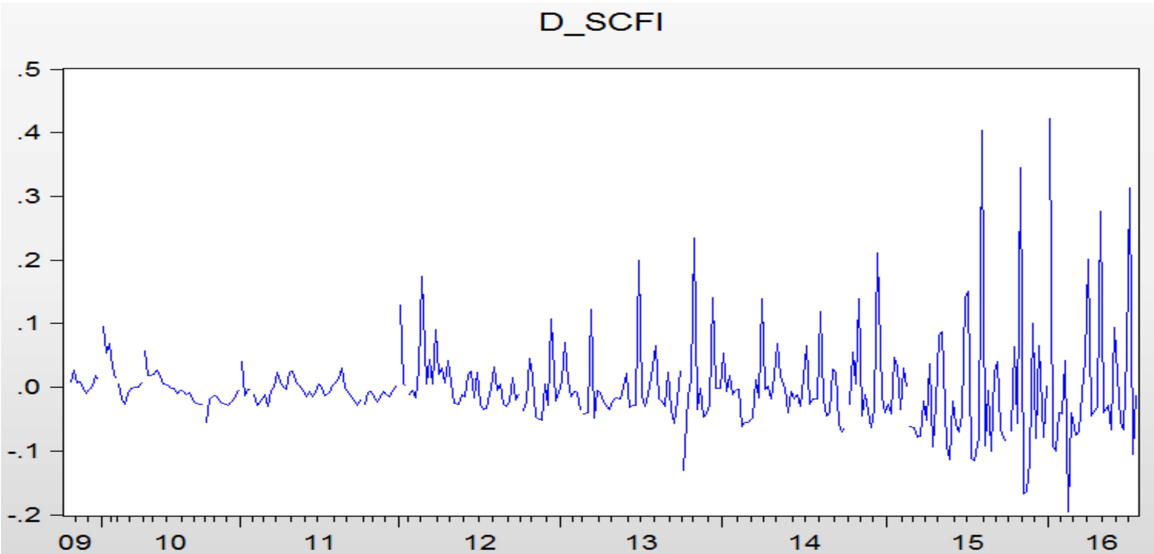

Figure 5

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Trends of logarithmic returns of BDTI

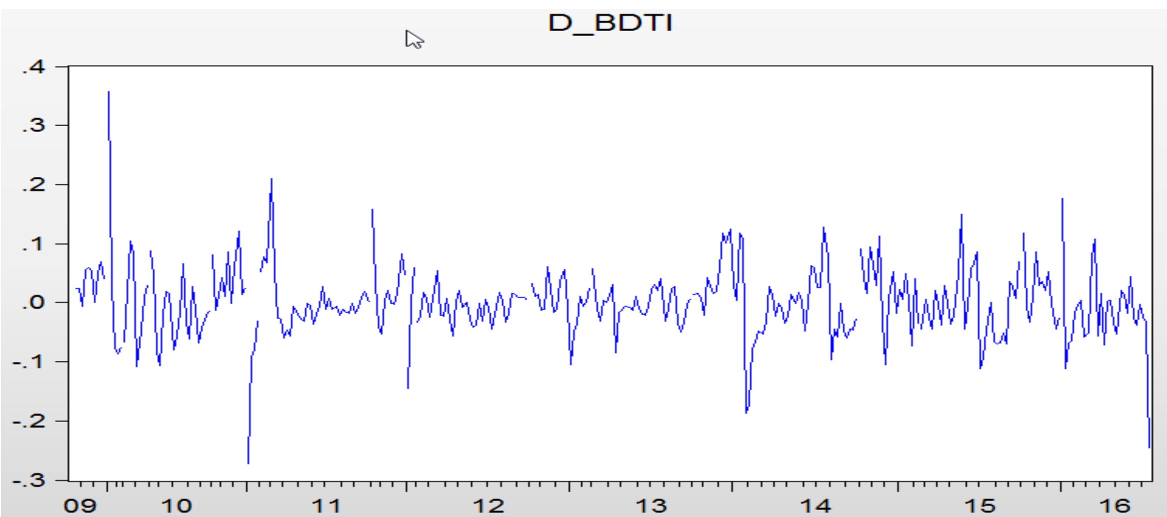

Figure 6

It is clearly revealed from above Figure 4, 5, and 6 that the BDI logarithmic return rate is comparatively more volatile than SCFI logarithmic return rates and BDTI logarithmic return rates. This is mainly because of sluggish recovery in demand for raw materials after the financial turmoil in 2008 and increasing shipping capacity. On the contrary, due to oligopolistic market characteristics, there is smooth volatility in the container shipping market. However, there is relatively large positive and negative spike in the SCFI index from July 2015 due to the implementation of Global Reporting Initiatives (GRIS)[6] and following the historical collapse of oil prices[7] seen over past few years (Lloyd's list Intelligence, may 2016). Moreover, a constant supply of container vessels also forced market rates to continue to face the introduction of large vessels on the main lane trade and cascading effect on non-main lanes trade. On the contrary, the tanker shipping market is a nearly- perfect competitive market where freight rates fluctuate significantly like the dry bulk market to some extent. The tanker freights rebounded from effects of the global financial crisis, albeit slightly in most case. Freight rates of tankers performed better in last two months of 2010, rising in 30 percent to 50 percent compare to the previous year due to increasing seasonal demand in the main energy consumptions market (Review of Maritime Transport, 2011). However, this fell sharply in the first week of 2011 due to high growth in the supply of tanker fleet. The BDTI performed better than the dry bulk and container freight index from mid of 2015, but it showed a sharp negative spike in July 2016 due to the sharpest growth in tanker fleet capacity by 8.5% and the mixed signal on the demand side (Lloyd's list Intelligence, July 2016). Therefore, the graph of indices indicates that the maritime industry is deeply affected by global economic changes. Although dry bulk shipping, container shipping, and tanker shipping belong to the maritime industry, the volatility trends of their log-returns rates have different patterns due to their unique industrial characteristics.

[6] GRIs is an international independent development organization that helps shipping players to communicate and understand the sustainability importance.
[7] Collapse of oil prices is mainly due to reduction in imports of oil by United States. So, Saudi, Nigerian and Algerian oil was once sold to US is now competing with Asian market, that caused in price drops of oil in 2015. Besides, the economies of Europe and developing countries are at slow pace ,and more development of fuel efficient vehicles has loomed the threat in demand side

3.2 Data analysis

In this literature, the weekly BDI, SCFI (comprehensive index), and BDTI data of 332 samples from 16th October 2009 to 15th July 2016 are used to explore the volatility transmission among dry bulk, container, and tanker (dirty) freight markets. All weekly samples of data for these three indices are sourced from Clarkson Shipping Intelligence Network. The BDI and the BDTI are published in London by the Baltic Exchange, whereas the SCFI are published from Shanghai Shipping Exchange. Several data of the BDI and the BDTI were not published on a particular date according to English and public holidays. Similarly, the SCFI were not published on some Chinese and public holidays. Consequently, this study does not consider those data for research, which was not published on a particular date even in any one of the indices.

All freight indices time-series data is transformed into a natural logarithmic return for analysis. This procedure reduces the variation of time-series data and makes it easier to fit in the model. It also enhances normalization by measuring all variables in comparable metrics, which enables evaluation of analytic relationship among variable despite the origin of data series. Eviews 9.0 software is employed to calculate all quantitative calculations in this study.

The table 5 illustrates the descriptive statistics of the logarithmic first difference of the BDI, the BDTI, and the SCFI. Sample means are statistically zero for all three indices, indicate that there is marginally upward movement in freight market due to impact of inertia of the financial tsunami. In addition, the most volatile series, based on standard deviation values are the BDI, which exhibits higher value (0.08468) compared to the BDTI and the SCFI. Dry bulk market respond quickly to economic turmoil as it mainly related to raw materials and domestic demands. However, the standard deviations of SCFI are significantly higher than the BDTI. The BDI skewness coefficient is lower than zero, indicating that the samples are mainly distributed on left sides of the mean. On the other hand, the SCFI and the BDTI present a right-skewed allocation, as their skewness co-efficient is positive and greater than zero. Regarding kurtosis, the value of these three indices is greater than 3, which means that data series have a peak near average point, decline rather rapidly, and have heavy tails. The kurtosis co-efficient of SCFI is slightly less than twice of BDTI, whereas the BDTI is more than double of the BDI. The discrepancy between skewness and kurtosis among freight indices series highlights a distributional facet of these three sectors of the maritime industry. The Jarque-Bera (J-B) value of three logarithmic return rates indicates departures of normality for the BDI, the BDTI, and the SCFI at 1% significance level. Furthermore, the Ljung-Box Q-statistics (Ljung & Box, 1978) of the first 36 lags of sample autocorrelation indicate significant serial correlation in all indices series. The existence of serial correlations in indices may attribute the way panelists and shipping companies or brokers provide information about freight rates for specific routes to calculate indices. These rates are based either on the actual fixture or, in the absence of an actual fixture, made on the average of the previous week's level.

Table 5 Descriptive statistics of Logarithmic return of Indices (BDI, BDTI, & SCFI).

	N	Mean	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	Q(36)
BDI	332	-0.00394	0.08443	-0.108804	3.7874	9.9766	252.13
						[0.006]	[0.000]
BDTI	332	-0.00020	0.05961	0.373556	8.9793	497.35	66.131
						[0.000]	[0.000]
SCFI	332	-0.00120	0.06952	2.447293	14.061	2003.798	130.91
						[0.000]	[0.000]

Note: All series are measured in logarithmic first differences.
• Figures in square brackets [] demonstrates exact significance levels.
• N is the number of observations.
• Skewness and Kurtosis are the estimated centralized third and fourth moments of the data.
• Q (36) and Q^2 (36) are the Ljung and Box (1978) Q statistics on the first 36 lags of the sample autocorrelation function of the logarithmic return series and of the squared logarithmic return series; these tests are distributed as χ^2 (36). The critical values are 58.11 and 51.48 for the 1% and 5% levels, respectively.
• J–B is the Jarque and Bera (1980) test for normality, distributed as χ^2 (2).

4. Methodology

4.1 Unit root test

The early and pioneering work to figure out the integration order of time series was done by using the Augmented Dickey–Fuller (ADF, 1981). The main purpose of this test is to explore the null hypothesis that $\phi = 1$ in the following equation (1.1) against the one-sided alternative $\phi < 1$(Brooks, 2014).

$$y_t = \phi y_{t-1} + u_t \qquad (1.1)$$

Thus, hypothesis of concern are H_o: series containing unit root versus, H_1: series is stationary. This hypothesis is examined by a set of additional test statistics and their critical values (Brooks, 2014). The test statistics for ADF tests are given as

$$test\ statistics = \hat{\phi}/S\hat{E}(\hat{\phi}) \qquad (1.2)$$

Furthermore, Phillips and Perron (PP, 1988) have advanced a more comprehensively theory of unit root test .The tests are similar to the ADF tests, but they include an automatic correction method to the ADF tests to allow for autocorrelated residuals (Brooks, 2014, p. 364). However, Kwiatkowski et al. (KPSS, 1992)[8] has proposed a stationary test to examine null hypothesis (H_o) that series are stationary versus series are non-stationary (H_1).

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[8] ADF tests and PP tests are poor at deciding, when the series is stationary but with a root close to the non- stationary boundary, for example, whether $\varphi=1$ or $\varphi=0.95$, especially with small sample sizes. As, they have low power. So, KPSS tests are used to get around this problem as a stationary tests as well as a unit root test.

In order to reject the null hypothesis, either the absolute value of test statistics should be more than the critical value and/or probability should be less than 0.05 for 95% of confidence level (Brooks, 2014).

So, this study has employed ADF tests, PP test and KPSS test to test the stationarity of variables and order of integration.

4.2 Co-integration test

According to Engle and Granger (1987), if two or more variables that are individually non-stationary, (*I(1)*) are linearly combined, then the combination will also be *I(1)*[9], then series are said to be co-integrated (Hsiao, Chou, & Wu, 2013). The economic justification is that if some variables are co-integrated, then these variables will exhibit a long-run equilibrium. Therefore, the co-integration test in the study is used to examine the long-run equilibrium relationship among dry bulk, container and (dirty) tanker shipping freight indices. Since it is possible that, in the short run, co-integrating variables may have some deviations, but their association would return in the long-run

Johansen (1988) and Johansen and Juselius (1990) proposed a statistical procedure to determine the model has that has r vectors of co-integration. This approach is based on multivariate technic of canonical relation, and the likelihood ratio test for co-integration vectors involves derivation of squared canonical correlations between regression residuals, which require calculation of eigenvalues[10] (Visvikis, 2016).

There are two test statistics for co-integration test based on this approach, which is formulated as

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{p} \ln\left(1 - \hat{\lambda}_i\right) \qquad (2.1)$$

and,

[9] I(1) stands for freight indices which is integrated of order 1 i.e. must be differenced once to become stationary.
[10] The Canonical correlations analysis is trying to find a linear combinations of a set of variables ,such that correlations among variables is maximized.

$$\lambda_{max(r,r+1)} = -T\ln(1-\hat{\lambda}_{r+1}) \quad (2.2)$$

Where r is the number of co-integrating vectors under the null hypothesis and $\hat{\lambda}_i$ is the estimated eigenvalue of the $\prod$ matrix and T is the number of observation. λ_{trace} is a joint test where null hypothesis is that the number of co-integrating vectors is less than or equal to *r* against an alternative that there are more than *r.* However, λ_{max} tests the null hypothesis that there are r co-integrating vectors, against alternative r+1. Critical values for λ_{trace} and λ_{max} are provided by Osterwald-Lenum (1992) (Brooks, 2014). If test statistics are greater than the critical value, then the hypothesis is rejected. Besides, null hypothesis may also be rejected if MacKinnonson-Haug-Michellis (1999) probability is less than 5% in case of 95% confidence interval (Brooks, 2014).

It should be economically justified in the selection of an optimal number of lag lengths. Moreover, according to Schwert (1987), if the lag number is too large, the model will reduce freedom and result inefficient estimates due to over parameterization. Likewise, if the lag number is too small, it will produce bias result due to parsimonious parameterization (Hsiao, Chou, & Wu, 2013). Therefore, this study uses the Schwaz's (1978) Bayesian information criterion (SBIC) method to determine the optimal lag numbers since SBIC is strongly consistent and will asymptotically deliver the correct model order.

$$SBIC = \ln(\hat{\sigma}^2) + \frac{K}{T} lnT \quad (2.3)$$

Where, $\hat{\sigma}^2$ is the residual variance, k is the total number of parameter estimated and T is number of observations.

4.3 VAR model and Granger causality tests

4.3.1 VAR model

A VAR is a simple regression model that can be recognized as an amalgam of univariate time series model and the simultaneous equations model (Brooks, 2014, p. 326). To illustrate, a bivariate VAR considers a set of two variables (y_t, z_t), each of whose current values depends on different combinations of previous *k* values of both variables, and error terms.

$$y_t = \sum_{i=1}^{p} A_{11}(i) y_{t-1} + \sum_{i=1}^{p} A_{12}(i) z_{t-1} + \varepsilon_{y,t} \qquad (2.4a)$$

$$z_t = \sum_{i=1}^{p} A_{21}(i) y_{t-1} + \sum_{i=1}^{p} A_{22}(i) z_{t-1} + \varepsilon_{z,t} \qquad (2.4b)$$

Where $\varepsilon_{y,t}$ and $\varepsilon_{z,t}$ are uncorrelated white noise term and $A_{k,j}(i)$ (k, j =1,2 ; i = 1,2, ..p) are coefficients. This system (VAR model of order p) can also be written as:

$$X_t = A_1 X_{t-1} + A_2 X_{t-2} + A_3 X_{t-3} + A_4 X_{t-4} + \cdots + A_p X_{t-p} + \varepsilon_t \qquad (2.5)$$

Where X_t is 2x1 vector of variables (y_t, z_t)', and ε_t is 2x1 vector of residuals ($\varepsilon_{y,t}$, $\varepsilon_{z,t}$)' which are normally distributed with zero mean and variance / covariance matrix ∑ and $A_{i,}$ (*i* = 1,2,3,…….p) are 2x2 matrices of coefficients:

$$A_i = \begin{bmatrix} A_{11}(i) & A_{12}(i) \\ A_{21}(i) & A_{22}(i) \end{bmatrix}$$

4.3.2 Granger causality test

This study will use the granger causality test to identify whether two variables move one after other or contemporaneously. Although, VAR model can estimate significant effects of sets of variables on each dependent variables, but it will be difficult to estimate when VAR includes many lags of variables (Brooks, 2014, p. 333). In order to confront this problem, Granger (1969) proposed causality tests for the analysis of the casual and lead-lag relationship between time series variables by restricting all of the lags of a particular variable to zero. The model in this study can be specified as follows:

$$y_t = \alpha_\circ + \sum_{i=1}^{p} \alpha_{1i} y_{t-i} + \sum_{j=1}^{q} \alpha_{2j} z_{t-j} + \varepsilon_{1t} \quad (2.6)$$

$$z_t = \beta_\circ + \sum_{i=1}^{p} \beta_{1i} z_{t-i} + \sum_{j=1}^{q} \beta_{2j} y_{t-j} + \varepsilon_{2t} \quad (2.7)$$

Where (y_t, z_t) are variables, p and q are optimal lag numbers, α and β are the regression coefficients, and ε_t is white noise disturbance term. This model tests null hypothesis ($H_\circ = \alpha_{21} = \alpha_{22} = \alpha_{23} = \ldots = \alpha_{2q} = 0$) that y_t would have no Granger effect on z_t against alternative that has Granger effect. If the null hypothesis is rejected it indicates that the lag of y_t has significant effect on z_t, which means that independent variable is leading dependent variable. It also tests whether z_t has Granger impact on the null hypothesis of y_t ($H_\circ = \beta_{21} = \beta_{22} = \alpha\beta_{23} = \ldots = \beta_{2q} = 0$). Again, if null hypothesis is rejected then, it indicates that z_t has causal relationship with y_t , representing that z_t is leading y_t . Moreover, if both null hypotheses are rejected, it indicates that these two variables have mutually influencing relationship. However, two variables are mutually independent if both null hypotheses are not rejected.

4.4 VECM model

In order to determine long-run causal relationship among co-integrated variables, this study has considered the VECM model. The VECM model can be formulated from VAR equation as following:

$$\Delta X_t = \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-1} + \prod y_{t-p} + \varepsilon_t \qquad \varepsilon_t \mid \Omega_{t-1} \sim \text{distr.}(0, H_t) \quad (2.8)$$

Where, $\Gamma_i = \left(\sum_{j=1}^{i} A_i\right) - I_2$, $\prod = (\sum_{i=1}^{p} A_i) - I_2$, and I_2 is 2x2 identity matrix. Δ denotes first order difference operator

The cointegration test between y_t and z_t is determined by estimating rank of matrix via its eigenvalues[11]. The rank of matrix is equal to eigenvalues roots that are not equal to zero.

If rank(Π) = 0, then Π is the 2x2 zero matrix suggesting that there are no any co-integrating relationships between y_t and z_t; in this case the equation is reduced to a VAR model in first differences (Brooks, 2014, p. 388). If rank (Π) = 2 (full rank), then all the variables in X_{t-1} are stationary and a VAR model in levels is estimated. If rank (Π) = 1 (reduced rank), then there is a single co-integration relationship between y_t and z_t, which is given by any row of matrix Π and the expression ΠX_{t-1} is the error-correction term. Π is product of two matrices, α and β', of dimension (2x1) and (1x2), respectively (Brooks, 2014, p. 388).

$$\prod = \alpha\beta' \tag{2.9}$$

Where, matrix β indicates the co-integrating vectors; α represents amount of each co-integrating vector entering in each equation of the VECM.

Furthermore, there must be existence of causality at least in one direction if two variables are co-integrated (Granger, 1988). In order to determine short- and long-run equilibrium relationship between y and x requires: (i) some of co-efficient of y_{t-i} in equation should be non-zero (short-run) and /or (ii) Co-efficient of vector error correction term must be significant and negative (long –run)[12].

[11] The eigenvalues used in test statistics are taken from rank-restricted product moment matrices and not of ∏ itself.

[12] The Johansen (1988) procedure is preferred because it provides more efficient estimates of the co-integration vector than the Engle and Granger (1987) two-step approach. Toda and Phillips (1993) argue that causality tests based on OLS estimators of unrestricted levels VAR's are not very useful in general because of uncertainties regarding the relevant asymptotic theory and potential nuisance parameters in the limit. However, maximum likelihood estimators based on Johansen's (1988, 1991) ML method (for large samples of more than 100 observations) are asymptotically median unbiased, have mixed normal limit distributions and take into account the

It should be noted that Granger-causality represents only a correlation between the present value of one variable and the lag values of others, which doesnot imply that movements of one variable cause movements of another (Brooks, 2014). Moreover, VAR still does not clarify the sign of the interrelation or to what extent these effects last, although its casualty examines whether the present estimation of variable X can be explained by the past estimations of variable Y. However, this study considers impulse response and variance decomposition to arrive further information.

4.5 Impulse response and variance decomposition

Block F-tests and casualty test in VAR or restricted VAR suggest only statistically significant impacts on the futures value of variable in model. It doesn't explain positive or negative effects on variable due to changes in other variable and how the lengths effects to work through the system. So, impulse response and variance decomposition in VAR is considered to examine such kind of information which is based on an exogeneity test.

In general, an impulse response indicates the responsiveness of any dynamic variables in the VAR to response to shocks to each explanatory variable (Brooks, 2014, p. 434). In particular, VAR's impulse responses mainly examine how the dependent variables react to unit shock applied to the error. Likewise, Variance decompositions define proportional movements in the dependent variables that are due to their own shocks versus shocks to the other variables (Brooks, 2014). It traces out the components of variances of dependent variables clearly. Meanwhile, variance decomposition analysis is also a vigorous tool to predict the changes of financial time-series series in future. But this is beyond this subject. Thus, this study concern variance decomposition as a confirmation of impulse responses. Generally, impulse responses analysis and variance decompositions offer almost similar information.

The concentrated effects of unit innovations are measured by relevant addition of the coefficients of the impulse response functions (Lin & Swanson, 2008).Henceforth, the

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information on the presence of unit roots in the system. Therefore, they are much better suited to perform inference.

ordering of the variable is most important for calculation of impulse response and variance decomposition. The optimal approach to overcome this problem is to generate orthogonalised impulse responses which attune the impact of a different ordering of the variables on impulse response functions (Brooks, 2014). Pesaran and Shin (1998) proposed a solution on ordering of variable by recommending the use of Generalized Impulse Response (GIR).This paper only mentions the graph of each financial freight indices series in response to various shocks. It doesn‘t refer to any calculation about the generalized impulse response functions.

4.6 Bivariate GARCH-BEKK model

4.6.1 VAR/VECM – GARCH –BEKK model

The variance of the residual terms is assumed to be constant (homoscedasticity) over time in the conventional econometrics model. But it is not practically valid in the case of the financial time series. Numerous financial time series have displayed the property of long-memory, which demonstrate the presence of significant correlations among long period separation variables (Harris and Sollis, 2003). Another distinguishing feature of the financial time series is known as ‘volatility clustering‘(Brooks, 2014). A plausible explanation of volatility clustering is that large (small) returns are expected to follow large (small) volatility.

Essentially, GARCH models can be employed to model the volatility of time-series variable (Brooks, 2014).This model is used to portray movements in conditional variance of an error term irrespective of limitation on parameterization of conditional mean equation. In addition, conditional covariance depends upon previous own lags.

This study examines the higher moment dependencies (volatility spillover) between freight indexes. For this purpose, the bivariate GARCH-BEKK with augmented positive parameterization is employed for analysis. The BEKK model has no requirement of positive definite conditional covariance matrix and residuals of data need not be comply with the distribution of N (0,1) unlike VECH-GARCH and DCC-GARCH model respectively. The mean equation of this model is parameterized either on VAR equation (2.4a &b) or VECM model equation (2.8). Based on the GARCH model (1,1) and GARCH (1,2), The specification of conditional variance matrix (H_t) are as follows:

$$H_t = CC' + A\varepsilon_{t-1}\varepsilon'_{t-1}A' + BH_{t-1}B' \tag{3.0}$$

For GARCH-BEKK (1,2) variance equations are:

$$H_t = CC' + A\varepsilon_{t-1}\varepsilon'_{t-1}A' + BH_{t-1}B' + DH_{t-2}D' \tag{3.1}$$

Where,H_t is a $N \times N$ conditinal variance matrix, *C* is a lower triangular matrix, *A, B* and *D* are estimated parameter matrices, ε_t is a $N \times 1$ residual vector, and *A', B', and C'* are $N \times N$ inverse co-efficient matrices. The matrix of *A* measures the degree of innovation of market *i* to *j* and captures the ARCH effects. Meanwhile, the elements in matrix B and D indicate persistence of volatility spillover between markets. In other words, the diagonal parameters in matrices capture the impact of own past stuns and volatility on its current conditional covariance. The off-diagonal elements of matrices A and B are measure the cross-impact on conditional variances and co-variances, which is also termed as 'volatility spillover' effects. This study considers diagonal BEKK model to analyze volatility transmission across the shipping market by limiting matrix A, B, and D as diagonal matrix.

Furthermore, the asymmetric GARCH-BEKK (1,1)model is employed to analyze volatility transmission, where conditional variance and/or conditional co-variances are allowed to react differently to positive and negative shocks of the same magnitude (Brooks, 2014). This model can be specified as:

$$H_t = CC' + A\varepsilon_{t-1}\varepsilon'_{t-1}A' + BH_{t-1}B' + D'Z_{t-1}Z'_{t-1}D \tag{3.2}$$

Where, $Z_t = -\varepsilon_{t-1} \quad \forall\ \varepsilon_{t-1} < 0$

The significant value of D in equation (3.2) indicate that the related market is more responsive to negative shocks than positive shocks of the same magnitude, which results in an increment of volatility.

4.6.2 Optimization and estimation of M-GARCH

In order to estimate the parameters of GARCH-BEKK model, quasi-maximum likelihood estimation (QMLE) is employed in this study. Since error terms (ε_t) is assumed as likelihood function of conditional student t-distribution, Baillie and Bollerslev (1995) proposed that student t-distribution error terms are not normally distributed for less than 4 degree of freedom (v < 4) (Kavussanos, Visvikis, & Dimitrakopoulos, 2014). The QMLE specification is as follows:

$$L(\theta) = -\frac{1}{2} log\left(\frac{\pi(v-2)\Gamma\left(\frac{v}{2}\right)^2}{\Gamma((v+1)/2)^2}\right) - \frac{1}{2} log\sigma^2{}_t - \frac{v+1}{2} log\left(1 + \frac{y_t - X'{}_t\theta)^2}{\sigma^2{}_t(v-2)}\right) \qquad (4.0)$$

Where, θ denotes all unknown estimated parameters and v is degree of freedom.

The optimization methods used in Eviews are based on the determination of first and second derivatives of log-likelihood functions with respect to the parameters at each iterations (Brooks, 2014, p. 434)[13]. The Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm with the Marquardt step method is used for optimization of log-likelihood function, which pushes the co-efficient estimates more quickly to their optimal value.

13 Optimization method based on first derivative is known as the gradient, while on second derivatives, it is known as Hessian.

5. Application and empirical analysis

5.1 Unit root test and stationary test

As discussed in methodology, the unit root test of natural logarithm and logarithmic return of freight indices are carried out by the ADF-test, the PP-test and the KPSS test of stationary. If magnitude of test-statistics is greater than magnitude of critical value (-0.2870 at 95 % of confidence interval for ADF- and PP-test), then the series is stationary and vice-versa. However, for the KPSS test, t-statistics should be less than the critical value (0.146 for 95 % of confidence level) for series to become stationary. Meanwhile, as mentioned before, the optimum lag length criteria are determined by SBIC information criteria. If contradictory result are achieved AIC is preferred. The summary of statistics is given on following table based on SBIC information criterion:

Table 6 Unit root test on log-level and logarithmic return series of freight indices[14]

Freight series	**ADF-Test**	**PP-test**	**KPSS-test**
BDI	-3.1727 (0.0225)	-2.0735 (0.2557)	1.348480
BDTI	-5.0528 (0.0000)	-4.2160 (0.0007)	0.261420
SCFI	-1.6483 (0.4567)	-1.5933 (0.4848)	1.237251
D_BDI	-11.7898 (0.0000)	-9.02079 (0.0000)	0.050246
D_BDTI	-12.5084 (0.0000)	-12.9334 (0.0000)	0.058002
D_SCFI	-18.00171 (0.0000)	-18.02991 (0.0000)	0.092692

[14] Numbers in bracket represent probability value for different freight indices in ADF- and PP-test. And D_ indicates logarithmic return of related series respectively.

All three statistics from table 6 confirmed that logarithmic SCFI is non- stationary in level and stationary in first difference. In addition, BDTI is confirmed stationary in level from all these t-statistics. However, contradictory result comes in case of logarithmic series of BDI.As, it is non-stationary according to PP-test and KPSS-test, whereas it is stationary according to ADF-test (magnitude of t-statistics is greater than magnitude of critical value and p-value (0.02557) is lesser to 0.05). Since SBIC predicts less lag length than AIC, which cause omission of some significant parameter from estimation. That cause different results in some cases. Nevertheless, all these three unit root tests indicate that logarithmic BDI is non-stationary even when AIC information criterion is used for selection of optimal lag number[15]. To further estimation in this study, BDI and SCFI is considered as non-stationary series in log-level, while BDTI is taken as stationary series.

5.2 Optimal lag selection in VAR model

According to SBIC criterion, this study finds that the optimal number of lags between BDI and SCFI is two, the optimal number of lag for BDTI and SCFI is one, and the optimal number of lags between BDI and BDTI is one, as it can be seen from table 7, 8 and 9.

[15] For ADF-test, t-statistics is -2.5146 and p-value is 0.1129; for PP test, t-statistics is -2.19099 and p-value is 0.2101; in case of KPSS-test, t-statistics is 1.4533.

Table 7 VAR Lag order selection criteria between BDI and SCFI

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-4833.079	NA	3.14e+10	29.84617	29.86951	29.85548
1	-3796.131	2054.694	53446419	23.46994	23.53996	23.49789
2	-3740.515	109.5159	38863865	23.15132	23.26801*	23.19790*
3	-3739.165	2.640421	39505322	23.16769	23.33105	23.23289
4	-3734.220	9.616071	39276041	23.16185	23.37189	23.24569
5	-3728.571	10.91485	38879143	23.15167	23.40839	23.25414
6	-3722.488	11.67723*	38383816*	23.13881*	23.44221	23.25991
7	-3720.941	2.950652	38971262	23.15396	23.50403	23.29368
8	-3720.601	0.645128	39864049	23.17655	23.57329	23.33491

Note: * indicate lag order selected by criterion

LR: Sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz Information Criterion

HQ: Hannan-Quinn information criterion

Table 8 VAR Lag order selection criteria between D_BDTI and D_SCFI

Lag	Logl	LR	FPE	AIC	SC	HQ
0	850.4314	NA	1.79e-05	-5.253445	-5.230054	-5.244108
1	867.3170	33.45767	1.66e-05	-5.333232	-5.263059*	-5.305220
2	874.3430	13.83440	1.62e-05	-5.351969	-5.235014	-5.305282
3	882.9606	16.86161*	1.58e-05	-5.380561	-5.216823	-5.315199*
4	887.4555	8.739363	1.57e-05	-5.383625	-5.173106	-5.299588
5	891.7515	8.299500	1.57e-05	-5.385458	-5.128157	-5.282747
6	895.7894	7.750723	1.57e-05*	-5.385693*	-5.081609	-5.264306
7	898.5820	5.325732	1.58e-05	-5.378216	-5.027351	-5.238155
8	899.1864	1.145165	1.62e-05	-5.357191	-4.959543	-5.198455

Note: * indicate lag order selected by criterion

LR: Sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz Information Criterion

HQ: Hannan-Quinn information criterion

Table 9 VAR lag selection criteria between D_BDI and D_BDTI

Lag	LogL	LR	FPE	AIC	SC	HQ
0	794.6626	NA	2.53e-05	-4.908127	-4.884736	-4.898790
1	877.5991	164.3325	1.55e-05	-5.396899	-5.326725*	-5.368886*
2	884.4488	13.48734	1.53e-05*	-5.414544*	-5.297589	-5.367857
3	884.8920	0.867227	1.56e-05	-5.392520	-5.228783	-5.327158
4	891.1841	12.23346*	1.54e-05	-5.406713	-5.196193	-5.322676
5	894.3342	6.085568	1.55e-05	-5.401450	-5.144148	-5.298738
6	899.1091	9.165609	1.54e-05	-5.406249	-5.102165	-5.284862
7	901.3127	4.202397	1.56e-05	-5.395125	-5.044259	-5.255063
8	902.3047	1.879548	1.59e-05	-5.376499	-4.978852	-5.217763

Note: * indicate lag order selected by criterion

LR: Sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz Information Criterion

HQ: Hannan-Quinn information criterion

5.3 Co-integration test

The estimated λ_{max} and λ_{trace} statistics in Table 10 illustrates that there is a long-run relations between BDI and SCFI and have a co-integrated relationship in the full sample period. There is one co-integrating equation between dry bulk and container freight markets in this model.

Table 10 Cointgration test of BDI and SCFI

Trace test	**Eigenvalues**	**Trace statistics**	**(0.05) Critical value**	**Probability**
None *	0.045047	17.33083	15.49471	0.0262
At most 1	0.006563	2.166276	3.841466	0.1411
Maximum Eigenvalues test	**Eigenvalues**	**Max- Eigen statistics**	**(0.05) Critical value**	**Probability**
None *	0.045047	15.16455	14.26460	0.0359
At most 1	0.006563	2.166276	3.841466	0.1411

5.4 Lead-lag relationship between shipping freight markets

5.4.1 Dry bulk and container freight market

The Granger causality test is used in the restricted VAR model to investigate whether there is a two-way feedback relationship or one-way lead-lag causality, or they are mutually independent. The result showed that they are mutually independent and have no significant lead-lag relationships. As from table 11, it is clearly noted that both hypothesis are rejected because t-statistics are less than critical value of chi-square distribution (3.841). In addition, p-value of t-statistics is greater than 0.05 which is strongly recommended to accept the hypothesis in both cases.

Table 11 VEC Granger Casuality test between D_BDI and D_SCFI

Dependent Variable: D (BDI)			
Excluded	**Chi-square**	**Degree of freedom**	**Probability**
D(SCFI)	1.144158	2	0.5644
All	1.14458	2	0.5644
Dependent Variable: D (SCFI)			
Excluded	**Chi-square**	**Degree of freedom**	**Probability**
D(BDI)	0.905588	2	0.6358
All	0.905588	2	0.6358

5.4.2 Dry bulk and tanker (dirty) freight markets

The t-statistics of chi-square distribution for VAR Granger causality show that these two shipping freight markets have no causal relationships and they are mutually independent series. It can be clearly predicted from following table 12.

Table 12 VAR Granger Causality test between D_BDI and D_BDTI

Dependent Variable: D (BDI)			
Excluded	**Chi-square**	**Degree of freedom**	**Probability**
D(BDTI)	2.838027	1	0.0921
All	2.838027	1	0.0921
Dependent Variable: D (BDTI)			
Excluded	**Chi-square**	**Degree of freedom**	**Probability**
D(BDI)	0.012631	1	0.9105
All	0.012631	1	0.9105

5.4.3 Container and (dirty) tanker freight markets.

Similar to the previous mentioned two Granger causality results, this test also has the same result. There is no lead-lag relationship between container and tanker (dirty) freight markets, which can be clearly illustrated from Table 13.

Table 13 VAR Granger Causality test between BDTI and SCFI

Dependent Variable: D (BDTI)			
Excluded	**Chi-square**	**Degree of freedom**	**Probability**
D(SCFI)	1.100435	1	0.2942
All	1.100435	1	0.2942
Dependent Variable: D (BDTI)			
Excluded	**Chi-square**	**Degree of freedom**	**Probability**
D(BDTI)	0.759795	1	0.3834
All	0.759795	1	0.3834

5.5 Impulse response and variance decomposition

A more detailed insight into the causal relationship between shipping freight markets is obtained by analyzing the impulse response and variance decomposition function of VAR model. This measures the response of one freight market to standard deviation shock to another shipping freight market. Since Eviews use ‘ordering of Cholesky’ as default for estimation of variance decomposition of variables. Henceforth, regarding ordering of variables, this study incorporates 'Cholesky with adjusted degree of freedom' methods for ordering for impulse response also.

Figures 7 to 12 illustrate the impulse response functions to capture the dynamics of shipping freight rates. 30-weeks ahead responses of one freight series to one standard deviation innovations of another freight series are calculated to obtain robust VAR estimates. Figures 7 & 8 depict the impact of shocks on dry bulk market. Furthermore, responses of container market in coming shocks are shown from Figure 9 & 10. While reaction of tanker freight markets are explained from Figures 11 & 12. Based on the previous analysis, this study only reports the figures of impulse response for significant results in Granger causality tests.

The dry bulk freight market shows positive response to the shock coming from itself for next 10 weeks, which gradually die out after these periods. While response of BDI is negative for next 3-4 weeks and then show a neutral reaction for the long-run in case of shock coming from the container freight market. This confirms the granger causality test that there is no lead-lag relationship between BDI and SCFI in the long-run. Furthermore, it is an almost neutral response for short duration by the bulk freight market to the shock coming from the tanker freight market and then it shows no any response after 10 weeks.

Regarding responses of the container freight market, SCFI shows positive response for a very short period and diminishes very fast when impulses are coming from BDI and BDTI. It indicates that the container freight market can adapt shocks quickly coming from other shipping freight markets. However, It shows stronger positive response for a short period and continue at neutral response for the long run from own shocks.

Moreover, BDTI shows neutral response to shocks coming from BDI while it shows negative reaction for first 4 weeks after positive shocks coming from container freight market. On the contrary, there is a positive impact of innovations on BDTI by itself for short period and then it captures very quickly.

Response of dry bulk freight market when shock coming from Container market and itself

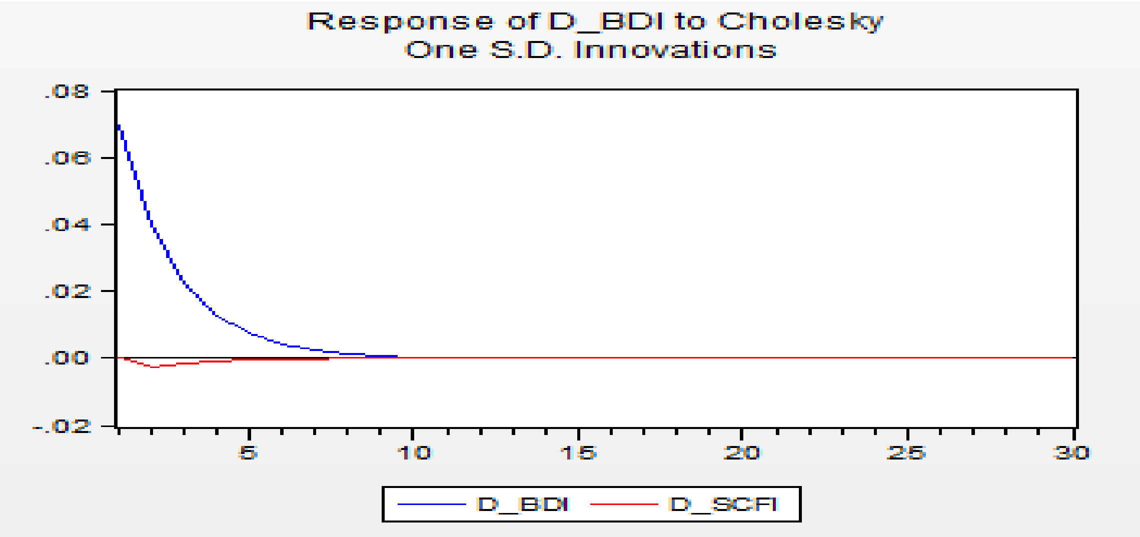

Figure 7

Response of dry bulk freight market when shock coming from tanker market and itself

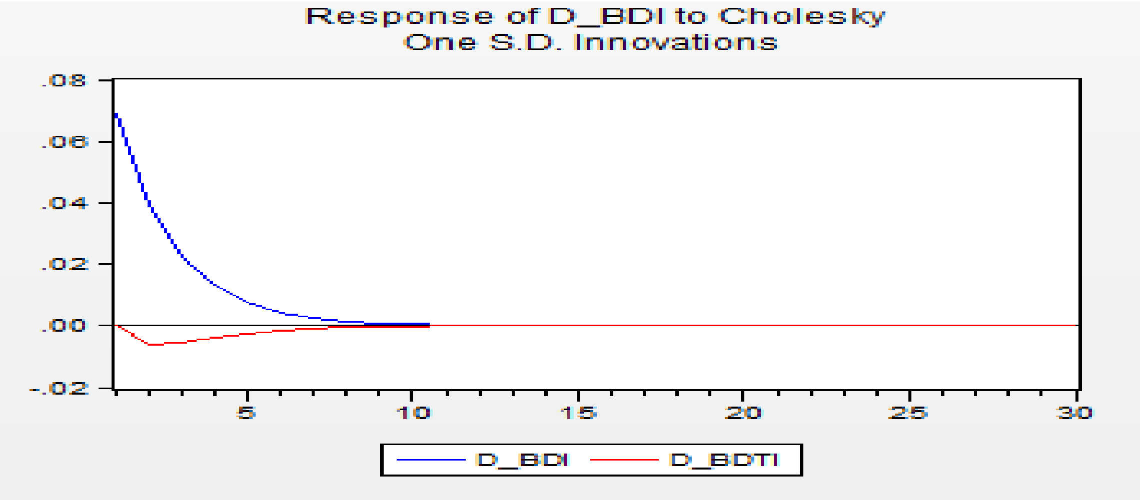

Figure 8

Response of container freight market when shock coming from tanker market and itself

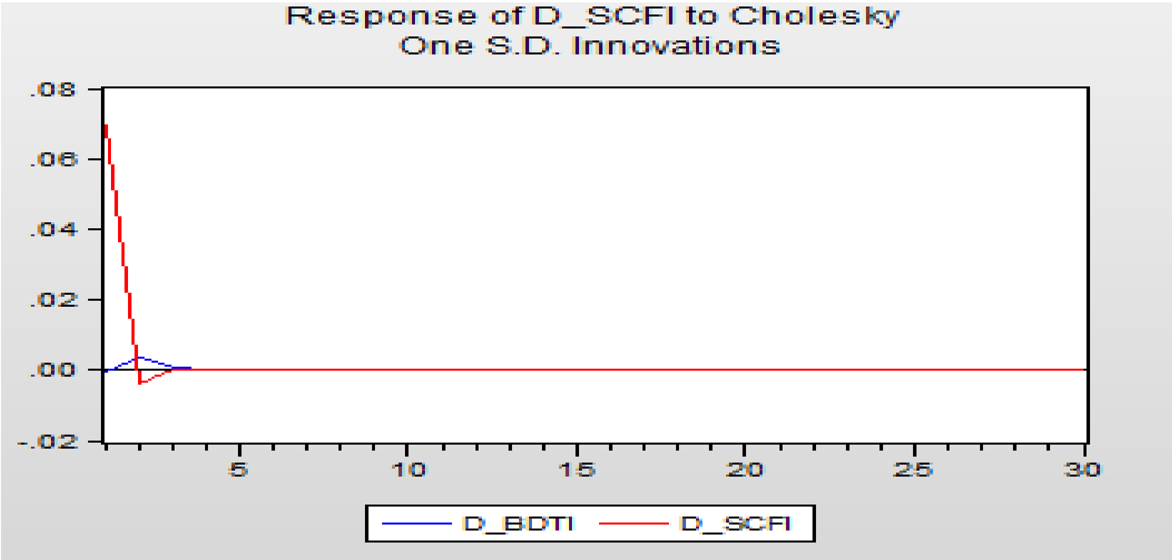

Figure 9

Response of container freight market when shock coming from dry bulk market and itself

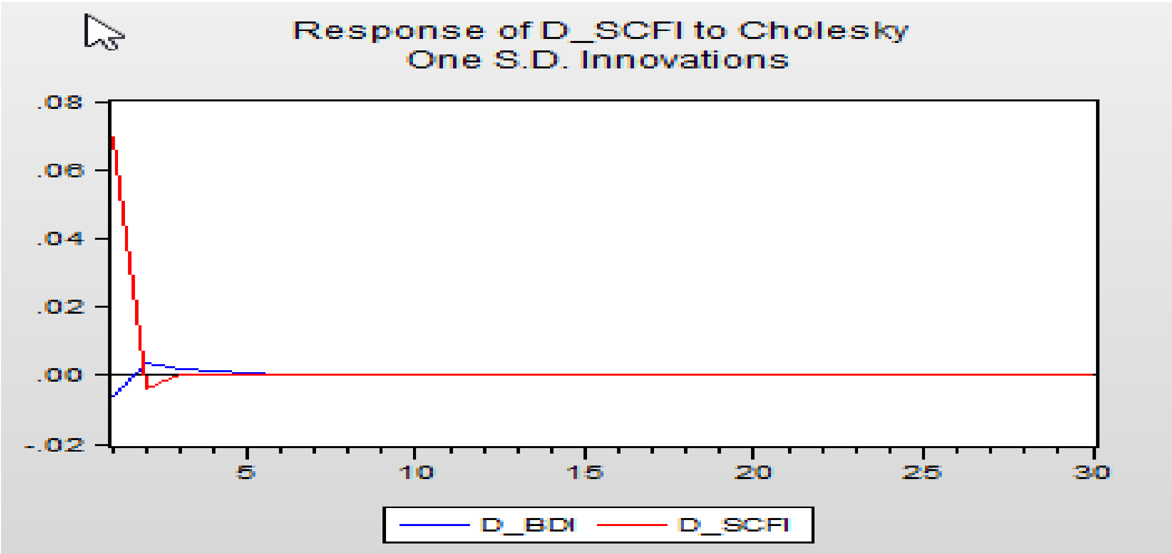

Figure 10

Response of tanker freight market when shock coming from dry bulk market and itself

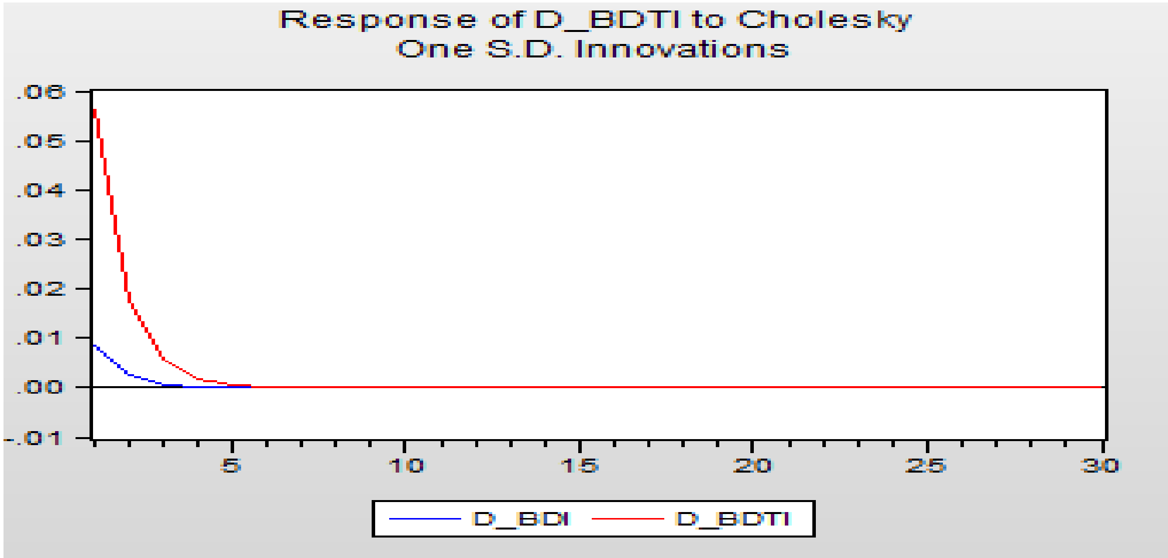

Figure 11

Response of tanker freight market when shock coming from Container market and itself

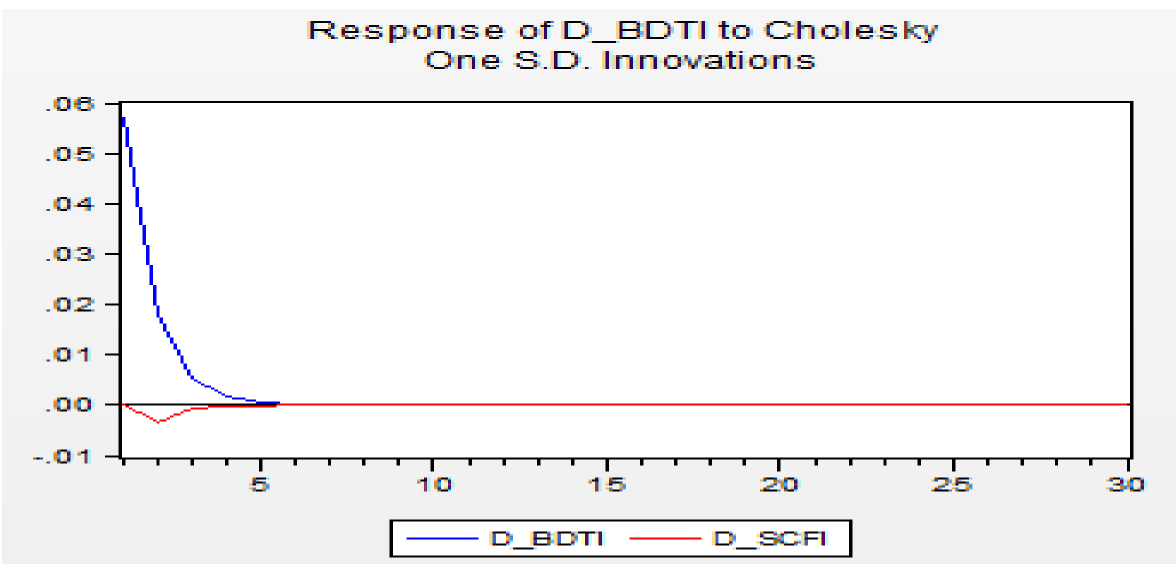

Figure 12

Variance decomposition of the shipping freight market for 10 ahead responses is depicted in Table 14. In general, it offers evidence of similar information with impulse response but it is often used for forecasting. To illustrate the justification of variance decomposition, the variance period 2 for decomposition of variance in container freight market is considered. In the short-run, there is a 98.89 percent variation of the fluctuation in return of SCFI due to own shock; shock to BDI can cause 0.94 percent fluctuations in the return rate of SCFI and an innovation in BDTI has only 0.15 percent impact on variation of fluctuation in return of SCFI. Whereas it is clearly depicted in the long-run that there are no more significant changes in percentage of fluctuation in SCFI due to dry-bulk and tanker-market innovations. Likewise, this is true for variance decomposition of the other two freight indices.

These results are in accordance with earlier results of causality tests, and confirm that there is no lead –lag relationship between any of the freight markets in long-run.

Table 14 Variance decomposition of shipping freight indices

Var.	Variance Decomposition of D_SCFI				Variance Decomposition of D_BDI				Variance Decomposition of D_BDTI			
Period	S.E	DBDI	DSCFI	DBDTI	S.E	DBDI	DSCFI	DBDTI	S.E	DBDI	DSCFI	DBDTI
1	0.06965	0.641	99.358	0.000	0.069	100.0	0.00	0.000	0.057	2.187	0.005	97.806
2	0.69912	0.944	98.896	0.158	0.079	99.27	0.120	0.608	0.059	2.165	0.284	97.550
3	0.06993	1.004	98.832	0.162	0.083	98.84	0.129	1.029	0.601	2.151	0.299	97.549
4	0.69941	1.023	98.814	0.162	0.084	98.64	0.129	1.219	0.060	2.149	0.301	97.549
5	0.69943	1.028	98.808	0.162	0.084	98.57	0.130	1.294	0.601	2.149	0.301	97.548
6	0.69944	1.030	98.806	0.162	0.084	98.54	0.130	1.321	0.601	2.150	0.301	97.548
7	0.69944	1.031	98.805	0.162	0.084	98.53	0.130	1.330	0.601	2.150	0.301	97.548
8	0.69944	1.031	98.805	0.162	0.084	98.53	0.130	1.334	0.601	2.150	0.301	97.548
9	0.69944	1.031	98.805	0.163	0.084	98.53	0.130	1.335	0.601	2.150	0.301	97.548
10	0.69944	1.031	98.805	0.163	0.084	98.53	0.130	1.335	0.601	2.150	0.301	97.548

Note: S.E represents standard deviation, D for logarithmic freight return

5.5 Bivariate GARCH-BEKK model

This paper employs bivariate diagonal GARCH-BEKK to effectively capture the own and cross volatility spillovers between shipping freight rate index. As discussed earlier, lower the information criterion better the model, so, lower SBIC has used in application of empirical for calculation of variance equations. Since, BDI and SCFI has co-integrated, the VECM-GARCH-BEKK (1, 2) model are applied to analyze volatility transmission between these freight markets. As there is serial correlation in lagged volatility term in container variance equation $(B_1(2{,}2) > 1)$ for VECM-GARCH BEKK (1,1), that makes the model explosive, which can be seen from Table 15.

Table 15 Estimated result of VECM- GARCH BEKK (1,1)

	Coefficient	Std. Error	z-statistics	Probability
C_1	-0.017656	0.008430	-2.094470	0.0362*
C_2	0.633091	0.060619	10.44380	0.0000*
C_3	-0.138397	0.058464	-2.367210	0.0179*
C_4	-0.052968	0.070247	-0.754026	0.4508
C_5	-0.064557	0.050518	-1.277884	0.2013
C_6	-0.005060	0.003581	-1.413108	0.1576
C_7	0.008425	0.002441	3.451735	0.0006*
C_8	-0.010410	0.014986	-0.694680	0.4873
C_9	-0.015710	0.012438	-1.263076	0.2066
C_{10}	0.239988	0.027052	8.871308	0.0000*
C_{11}	0.087526	0.014093	6.210754	0.0000*
C_{12}	-0.005974	0.000887	-6.7366176	0.0000*
M(1,1)	0.002686	0.001835	1.463841	0.1432
M(1,2)	-5.32E-06	7.46E-06	-0.712799	0.4760
M(2,2)	1.05E-08	2.59E-08	0.406360	0.6845
$A_1(1,1)$	0.513451	0.153160	3.352395	0.0008*
$A_1(2,2)$	-0.036135	0.026554	-1.360824	0.1736
$B_1(1,1)$	-0.713153	0.166948	-4.271700	0.0000*
$B_1(2,2)$	1.007097	0.001288	781.6375	0.0000*

Note: * represent significant at 5% significance level.

On other hand, due to unavailability of long-run equilibrium relations between dry–bulk and tanker (dirty) freight market, the bivariate GARCH-BEKK (1,1) model is employed with VAR mean equation to analyze fluctuation of volatility between these perfect competitive shipping freight markets. Similarly, asymmetric VAR-GARCH-BEKK (1, 1) model is considered to investigate the spill over relationship between the container and tanker (dirty) freight markets.

5.5.1 Volatility spillover effects between dry bulk and container freight market.

Regarding the conditional variance equation between BDI and SCFI, the short-run spillover effect and long-run transmission effect are estimated and summarized in Table 16. The mean equations, conditional variance equations and conditional covariance equation related to estimated results are as follows respectively:

VECM Mean Equations

$$\Delta BDI = C_1(BDI(-1) - 2.0494672\, SCFI(-1) + 785.4148) + C_2\Delta BDI(-1) + C_3\Delta BDI(-2) + C_4\Delta SCFI(-1) + C_5\Delta SCFI(-2) + C_6 \qquad (5.1)$$

$$\Delta SCFI = C_7(BDI(-1) - 2.0494672\, SCFI(-1) + 785.4148) + C_8\Delta BDI(-1) + C_9\Delta BDI(-2) + C_{10}\Delta SCFI(-1) + C_{11}\Delta SCFI(-2) + C_{12} \qquad (5.2)$$

Variance equations of GARCH

$$h_{BDI} = M(1,1) + A_1(1,1)^\wedge 2resid1(-1)^\wedge 2 + B_1(1,1)^\wedge 2GARCH1\,(-1) + B_2(1{,}1)^\wedge 2\, GARCH1(-2) \qquad (5.3)$$

$$h_{SCFI} = M(2,2) + A_1(2,2)^\wedge 2resid2(-1)^\wedge 2 + B_1(2,2)^\wedge 2\, GARCH2(-1) + B_1(2{,}2)^\wedge 2\, GARCH2(-2) \qquad (5.4)$$

Covariance equation

$$cov\ BDI\_SCFI = M(1,2) + A_1(1,1)A_2(2{,}2)resid1(-1)resid2(-2) + B_1(1,1)B_1(2{,}2)cov\ BDI\_SCFI(-1) + B_2(1{,}1)B_2(2{,}2)cov\ BDI\_SCFI(-2) \qquad (5.5)$$

Where, ΔBDI and ΔSCFI are logarithmic first difference of dry bulk freight index and container freight index respectively, M is matrix of constant

Table 16 Estimated result of VECM-GARCH-BEKK (1, 2)

	Coefficient	Std. Error	z-statistics	Probability
C_1	-0.009442	0.007170	-1.316840	0.1879
C_2	0.631919	0.061013	10.35719	0.0000*
C_3	-0.184183	0.058734	-3.135895	0.0017*
C_4	-0.044655	0.051030	-0.875075	0.3815
C_5	-0.037015	0.043885	-0.843455	0.3990
C_6	-5.158013	3.719847	-1.386620	0.1656
C_7	0.005496	0.001633	3.366090	0.0008*
C_8	-0.006601	0.005113	-1.291048	0.1967
C_9	-0.010996	0.006629	-1.658853	0.0971
C_{10}	0.219364	0.059615	3.679658	0.0002*
C_{11}	0.102387	0.012423	8.241815	0.0000*
C_{12}	-7.199407	1.134699	-6.344772	0.0000*
M(1,1)	463.8838	268.2202	1.729489	0.0837
M(1,2)	-7.761094	11.25957	-0.689289	0.4906
M(2,2)	0.129848	0.353866	0.366942	0.7137
$A_1(1,1)$	0.617078	0.105999	5.821555	0.0000*
$A_1(2,2)$	-0.202618	0.116348	-1.741475	0.0816
$B_1(1,1)$	0.857318	0.039778	21.55259	0.0000*
$B_1(2,2)$	0.760804	0.108781	6.993909	0.0000*
$B_2(1,1)$	-0.058158	0.272810	-0.213183	0.8312
$B_2(2,2)$	0.630966	0.127096	4.964499	0.0000*

Note: * represent significant at 5% significance level.

From mean equations statistics, it indicates that current period's freight return has been jointly effected from own last two lagged freight returns in both freight markets. A standard Wald test is employed to test jointly significance of estimated co-efficient on lagged freight return on current freight return. The Co-integrating term is insignificant for BDI (C_1) which shows that there is no long run relationship from the container freight market to the dry-bulk freight market. However, it is significant but slightly positive for container freight market(C_7), which implies that SCFI responds to the previous deviation but doesn't do all corrections to eliminate the disequilibrium. Furthermore, the highly significant value of 0.6170 ($A_1(1,1)$) suggests that there is positive response in volatility of dry bulk freight return due to presence of shock in return. However, volatility of container freight return showed insignificant response of to the lagged freight rate returns in the short-run impact. Regarding long-run volatility transmission, current period's BDI return volatility shows presence of volatility of clustering for only previous lagged freight return volatility, that is the high current volatile market is followed by the high volatile market of one lagged freight return. This is statistically shown by the significant values of one lagged term only at -0.7133($B_1(1,1)$).

Furthermore, the container freight market show highly strong volatility clustering as co-efficient of $B_1(2,2)$ and $B_2(2,2)$ are highly significant with large value i.e. 0.7608 and 0.6309 respectively. This large value of lagged container freight return volatility state that it will take a long time to fade out.

Regarding the volatility spillover effect between BDI and SCFI, covariance equation estimated result shows that $(B_1(1,1))$ and $B_1(2,2)$ are only statistically significant to explain that there is existence of spillover effect of one lagged freight return of BDI on the current SCFI return and the lagged SCFI return has significantly impact on return of BDI in the current period.

5.5.2 Volatility spillover effects between container and tanker freight market

Like the previous model, variance equations and covariance equations are estimated in the GARCH-BEKK (1, 2) model to investigate volatility in the freight return market. Since there is no co-integration relation between container and tanker freight markets, the VAR model is employed to estimate mean equations. The specification of mean equations, variance equation and covariance equations are as follows:

VAR mean equation

$$\Delta BDTI = c_1 \Delta BDTI(-1) + C_2 \Delta SCFI(-1) + C_3 \qquad (5.6a)$$

$$\Delta SCFI = C_4 \Delta SCFI(-1) + C_5 \Delta BDTI(-1) + C_6 \qquad (5.6b)$$

Variance equation in GARCH-BEKK (1, 2)

$$h_{BDTI} = M + A_1(1,1)^\wedge 2\ resid1(-1)^\wedge 2 + B_1(1,1)^\wedge 2\ GARCH1(-1) + B_2(1,1)^\wedge 2\ GARCH1(-2) \qquad (5.7a)$$

$$h_{SCFI} = M + A_1(2,2)^\wedge 2 resid2(-1)^\wedge 2 + B_1(2,2)^\wedge 2\ GARCH2(-1) + B_2(2,2)^\wedge 2\ GARCH2(-2) \qquad (5.7b)$$

Covariance equation

$$COV_{BDTI\_SCFI} = M(1,2) + A_1(1,1)A_2(2,2)resid1(-1)resid2(-2) + B_1(1,1)B_1(2,2)cov\ BDTI\_SCFI(-1) + B_2(1,1)B_2(2,2)cov\ BDTI\_SCFI(-2) \quad (5.8)$$

From mean equation estimated result in Table 17 , it is clearly shown that any shock present in market (Positive or negative) volatility has positive impact in current freight return of the tanker and container freight markets, as co-efficient C_1 and C_5 have significant value of 0.3621 and 0.2510 respectively. From variance equation and covariance equation estimated result, only $B_1(1,1)$ can be considered as significant as its p-value (0.0547) is close to 0.05, it means that previous (one lagged) freight rate return volatility of tanker has a transmission effect on the current period freight return volatility. Further, other co-efficients in variance equation and covariance equation have no significant value. So, there is no volatility transmission in the current period container freight return from lagged freight return and no volatility spillover effect between container and tanker freight markets.

Table 17 Estimated result summary of VAR-GARCH-BEKK (1, 2)

	Coefficient	Std. Error	z-statistics	Probability
C_1	0.362180	0.082255	4.403151	0.0000*
C_2	-0.019640	0.073999	-0.265404	0.7907
C_3	-0.000639	0.002863	-0.223208	0.8234
C_4	0.025138	0.035552	0.707087	0.4795
C_5	0.251089	0.115108	2.181339	0.0292*
C_6	-0.005166	0.001984	-2.604195	0.0092*
M	-1.21E-05	1.12E-05	-1.075322	0.2822
$A_1(1,1)$	0.415642	0.249081	1.668700	0.0952
$A_1(2,2)$	-0.060805	0.122702	-0.495554	0.6202
$B_1(1,1)$	0.729585	0.379673	1.921611	0.0547
$B_1(2,2)$	0.745889	0.458011	1.628539	0.1034
$B_2(1,1)$	0.597860	0.537335	1.112638	0.2659
$B_2(2,2)$	0.685989	0.500989	1.369271	0.1709

Note: * represent significant at 5% significance level.

5.5.3 Volatility spillover effects between dry bulk and tanker freight market

In order to investigate volatility transmission effects across dry bulk and tanker freight markets the asymmetric GARCH-BEKK (1, 1) model is employed. As discussed before, BDTI is stationary in level, so there is no long –run equilibrium (co-integrated) relations between dry-bulk and tanker freight markets. Thus, the VAR model is employed as mean equation in this multivariate GARCH. The specifications of various equations for this model are as follows:

VAR mean equations

$$\Delta BDI = c_1 \Delta BDI(-1) + C_2 \Delta BDTI(-1) + C_3 \qquad (5.9a)$$

$$\Delta BDTI = c_4 \Delta BDI(-1) + C_5 \Delta BDTI(-1) + C_6 \qquad (5.9b)$$

Variance equations of asymmetric GARCH-BEKK (1, 1)

$$h_{BDI} = M + A_1(1{,}1)^\wedge 2\ resid1(-1)^\wedge 2 + D_1(1{,}1)^\wedge 2\ resid1(-1)^\wedge 2\ (resid1(-1) < 0) + B_1(1{,}1)^\wedge 2\ GARCH1(-1) \qquad (5.10a)$$

$$h_{BDTI} = M + A_1(2{,}2)^\wedge 2\ resid2(-1)^\wedge 2 + D_1(2{,}2)^\wedge 2\ resid2(-1)^\wedge 2\ (resid2(-1) < 0) + B_1(2{,}2)^\wedge 2\ GARCH2(-1) \qquad (5.10b)$$

Covariance equation

$$COV_{BDI\_BDTI} = M(1,2) + A_1(1,1)A_2(2{,}2)resid1(-1)resid2(-2) + D_1(1{,}1)^\wedge 2\ D_1(2{,}2)^\wedge 2 resid1(-1)^\wedge 2\ (resid1(-1) < 0)\ resid2(-1)^\wedge 2\ (resid2(-1) < 0) + B_1(1,1)B_1(2{,}2)cov\ BDI\_BDTI \qquad (5.11)$$

Table 18 Estimated result summary of VAR GARCH-BEKK (1, 1)

	Coefficient	Std. Error	z-statistics	Probability
C_1	0.570402	0.055878	10.20807	0.0000
C_2	-0.139385	0.061844	-2.253821	0.0242
C_3	-0.003588	0.003651	-0.982734	0.3257
C_4	-0.013625	0.028002	-0.486563	0.6266
C_5	0.316995	0.059204	5.354251	0.0000
C_6	-0.001658	0.002196	-0.755129	0.4502
M (1,1)	0.004913	0.001634	3.007110	0.0026
M (1,2)	0.000320	0.000253	1.263599	0.2064
M (2,2)	0.000286	0.000223	1.284405	0.1990
$A_1(1,1)$	-0.311903	0.126161	-2.472256	0.0134
$A_1(2,2)$	0.417502	0.095020	4.393823	0.0000
$D_1(1,1)$	0.478795	0.209405	2.286454	0.0222
$D_1(2,2)$	-0.026808	0.026733	-1.002811	0.3160
$B_1(1,1)$	0.224387	0.558533	0.401744	0.6879
$B_1(2,2)$	0.864708	0.057869	14.94255	0.0000

Note: * represent significant at 5% significance level.

The estimated result in Table 18 showed that freight return of BDI in current period is reactive to previous shock in return of dry bulk market and (dirty) tanker market. However, it shows positive response to impulse in lagged return of dry bulk freight market while have negative reaction to presence of shock in previous freight return of tanker market due to presence of significant value of $C_1 = 0.57$ and $C_2 = -0.139$.Further, Lagged BDI return has a stronger impact than lagged tanker freight market on the current freight return volatility of dry bulk market. However, the significant value of C_5 at 0.316 suggests that current return volatility of BDTI will increase in presence of shock of tanker freight market. However, there is no response of short-run impact of lagged freight returns of the BDI on current tanker freight market.

There is long-run transmission effect of lagged BDI and BDTI freight return volatility in current period's freight rate return volatility of the dry bulk market, as the value of $A_1(1,1)$ is significant at -0.319. Similarly, $A_1(2,2)$ is highly significant at 0.417 indicating that lagged freight rate return volatility of tanker and dry bulk freight markets also have transmission effect on current period freight return volatility of tanker market. Besides, there is long-run mutual transmission impact of previous freight rate return volatility on the present freight rate return volatility across the dry bulk and tanker segment, as both

$A_1(1,1)$ and $A_1(2,2)$ are significant in covariance equation. Since the value of both co-efficient $(D_1(1,1)\,;D_2(2,2))$ of negative shock is not significant, it shows that negative shock generated within either market doesn't have effect of volatility on other market.

Furthermore, there is volatility transmission effect on current period's freight rate return volatility from own lagged period volatility in tanker freight market, as the value of $B_1(2,2)$ is significant at 0.86. This value is too large which means conditional volatility will take long time to fade out. On the other hand, insignificant value of $B_1(1,1)$ indicate that there is no transmission of volatility from own lagged period of dry bulk freight rate return on current period. Further, it also indicates that there is no volatility spillover effect on freight return in current period due to insignificant co-efficient of $B_1(1,1)$ in covariance equation.

5.6 Discussion

The significant findings of this study can be summarized as below:

First, the mean equation of the GARCH-BEKK model incorporated in this study along with impulse response and variance decomposition method indicates that in short run, dry bulk market has positive impact due to presence of own shock but has negative response to shocks coming from container freight for one or two week (see Figure 7). As discussed earlier the dry bulk freight rate is decided by market demand–supply equilibrium, it shows promptly positive reaction to the changes in economic climate. However, to meet the fast and emergency demand in shipping trade, container ships are in more demand for short duration of periods to transport bulk commodities like grain, coal, and iron. This is because of fast services provided by container ships, as these ships are faster in transportation and loading and discharging of cargoes than dry bulk ships. Consequently, it affects the demands of dry bulk market and its freight rate, whereas the container freight market shows neutral response to shocks in the dry bulk market due to its oligopolistic characteristics in the short-run but have positive response when impulse comes from its own market. As, top 20 service operators in the container shipping industry have a share of more than 84% of total shipping capacity by 2016 (Alphaliner, 2016), container shipping freight rate mechanism is largely influenced by these giant service operators rather than economic climate fluctuations. This causes a neutral response owing to shocks coming from dry bulk markets in the short-run. However, due to the characteristics of container shipping trade, freight rates can be flexible and negotiable between shippers and traders in the short-run. Furthermore, the tanker freight market reacts positively to own shock as well as shocks coming from the dry bulk market in the short run. However, duration and intensity of reaction in tanker freight market to the coming shocks from dry bulk is lower than its own shocks. This is due to fact that the demand of tanker market is mainly driven by economics of the oil markets and trade, the related macroeconomic variables of major economies, such as imports and consumption of energy commodities rather than the commodities market. Further, it shows neutral response to shocks coming from the container freight market. Meanwhile, the dry bulk freight market shows negative response in short run to shock coming from the tanker freight market. It can be clearly justified by the decline in oil price since mid-2014. This causes an increase in demand of the tanker market for transportation of oil and laying off vessel for storage of oil. Despite of lower oil prices, lower commodity price are leading to sizeable incomes which lead to postponing of households and business and spending investment decisions and cause cut off in demand of commodities (Rex, Andersen, & Kristensen, 2015).

Second, the Engle and Granger causality test shows that there is no lead-lag relationship among shipping freight markets after the financial tsunami in 2008 in long run. This is also strongly supported by the impulse response analysis and variance decomposition method. It implies that past information of one freight market doesnot play a significant role in prediction of current period freight of another market. This is due to fact that the fluctuations in shipping freight markets are not following the same trend to each other.

Third, dry bulk freight market volatility contains information from previous period freight rate impulse of dry bulk, container and tanker freight market. Also, its volatility also has a transmission effect from previous period freight volatility. After the financial crisis, the bulk shipping had not recovered due to the sluggishness demand of raw material and increasing capacity. Furthermore, dry bulk freight return volatility has also been affected to some extent due to collapse of oil price effects as discussed earlier. Also, this study find that there is a mutual volatility spillover effect between the dry bulk and container freight market after the financial tsunami in accordance with empirical work of Hsiao, Chou, and Wu (2013). This is due to the fact that demand of container and dry-bulk market is somehow interrelated due to common commodities of raw material, as container generally transport finished or semi-finished product made up of raw material.

Fourth, container freight return volatility has a transmission effect from the previous return volatility caused by the bulk and container freight markets. It shows high volatility clustering which means that high volatility is followed by high volatility. Since container shipping is close to oligopoly, in which the freight rate is determined by a small number of leading owners. Therefore, container freight rate moves up rather easily, but will move down with pronounced efforts. However, the trend of mega-ships in container shipping has increased fleet capacities which result into higher supply volume of container capacities compared to its demand in the market. That cause fall in freight rate due to excess supply in market. Hence, higher volatility transmission is followed by higher volatility and lower volatility is followed the lower volatility. Further, as discussed earlier container ships normally carry trade products in finished or semi-finished form of raw materials, which create an interrelation between container and dry bulk freight market. Henceforth, all these economic justifications are clear evidence of result found for transmission effect in container freight market.

Fifth, the current period of tanker freight return volatility shows positive reaction to the shock coming from previous period of the dry bulk and tanker markets. Further, regarding volatility transmission between the tanker and dry bulk markets, tanker freight return exhibits larger volatilities effects from previous period compared to dry bulk. This is due to the fact that shipping trade of crude oil are driven by contemporaneous market uncertainty (Tsouknidis, 2016). In addition, there is high persistence ($B_1(1,1) = 0.72$) of volatility in the current tanker freight market from lagged volatility caused by the tanker and container freight market, which takes long time to fade away (seeTable 17). However, the VAR-GARCH-BEKK (1, 2) estimated results show that there is no significant impact of container freight return on tanker freight return volatility. Thus, transmission of volatility in the current period in the tanker freight market from the previous period is strongly influenced by the tanker freight market compare to the container freight market. This is due to the fact that oil is majorly transported by tanker market, and container ships carry almost neglible amount of oil for transportation. Therefore, it results in occurrence of wild volatility transmission in tanker freight rates due to stronger impact of tanker market.

6. Conclusion

This study investigates the lead-lag relationships of BDI of dry bulk, SCFI of container, and BDTI of tanker (dirty) freight market and volatility transmission effects across these shipping freight markets. This study employed the GARCH-BEKK model to analyze the volatility transmission effect and the Johansen co-integration test and the Engle Granger causality test to examine the lead-lag relationships between shipping freight indices. Further, it also contributes to literature by examining volatility transmission effects and lead-lag relationship among these three shipping segment freight markets for the first time.

The empirical results suggest that there is no lead-lag relationship between any two shipping freight markets after the financial tsunami. However, there is one co-integrated vector between the dry bulk and container freight market, and they donot have causal effect relationship. In addition, the Impulse response analysis and variance decomposition method state that all three indices have positive impact of their own shocks in the short run. However, the dry bulk freight market has negative reaction to the shocks coming from the container and tanker freight market in the short-run. The container freight market has no reaction to shock coming from both the dry bulk and container market in the short–run due to its monopolistic competitive market behavior. Further, the tanker freight market shows positive response to shock coming from the dry bulk freight market but has no reaction to innovations in the container freight market in the short period.

In addition, the estimated results of models used in this study show that there is mutual volatility transmission effects between the dry bulk and container freight rate markets. However, there are no volatility spillover effects between the tanker market and the container freight market after the financial crisis and same is also true for the tanker and bulk freight market. However, there is also mutual transmission of any shock (positive or negative) between the tanker and dry bulk freight shipping sectors. Similarly, regarding the container and dirty tanker freight markets, any positive or negative impulse generated in either one market is transmitted to other.

Moreover, further studies can also consider other tanker indices like the BCTI, the Baltic international tanker routes (BITR) Asia along with BDTI to analyze more effective lead-lag relationship and volatility spillover effects between tanker freight markets to other shipping freight market incorporated in this study. As, this consideration reflect closer prediction of the tanker freight markets volatility transmission and interrelations to other shipping freight markets.

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