Econometric analyses of liquefied petroleum gas and product tanker shipping markets

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ECONOMETRIC ANALYSES OF LIQUEFIED PETROLEUM GAS AND PRODUCT TANKER SHIPPING MARKETS

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2019

ECONOMETRIC ANALYSES OF LIQUEFIED PETROLEUM GAS AND PRODUCT TANKER SHIPPING MARKETS

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A thesis submitted to the Nanyang Technological University
in partial fulfilment of the requirement for the degree of
Doctor of Philosophy

2019

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research, is free of plagiarised materials, and has not been submitted for a higher degree to any other University or Institution.

10 Jun 2019

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Bai Xiwen

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I have reviewed the content and presentation style of this thesis and declare it is free of plagiarism and of sufficient grammatical clarity to be examined. To the best of my knowledge, the research and writing are those of the candidate except as acknowledged in the Author Attribution Statement. I confirm that the investigations were conducted in accord with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

10 Jun 2019

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Lam Siu Lee Jasmine

Authorship Attribution Statement

This thesis contains material from 4 paper(s) published in the following peer-reviewed journal(s) / from papers accepted at conferences in which I am listed as an author.

Chapter 4.1 is published as X. Bai, and J. S. L. Lam. An integrated analysis of interrelationships within the very large gas carrier (VLGC) shipping market. *Maritime Economics and Logistics* (2017). DOI: 10.1057/s41278-017-0087-3.

The contributions of the co-authors are as follows:

- Prof Lam Siu Lee Jasmine provided the project direction, reviewed and edited the manuscript drafts.
- I prepared the manuscript drafts. The manuscript was revised by Prof Lam Siu Lee Jasmine.
- I collected the data and analyzed the data.

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SUMMARY

Today, crude oil is refined all over the world. However, there is a mismatch of refined products between supply and demand, among and within various regions due to the different numbers of refineries, refinery specifications and outputs, and demand in the region. Therefore, refined products need to be transported by sea to balance supply and demand, which constitutes an important part of the energy supply chain. This thesis aims to provide econometric analyses of product tanker and Liquefied Petroleum Gas (LPG) shipping markets - the dominant markets for refined product seaborne transportation.

This research starts with a review of past work on tramp shipping freight market modeling, identifying the major trends and methods in each topic. The existing research can be classified into four categories, namely supply-demand modeling, freight rate process modeling, freight rate forecasting and freight rate relationships. The study also reviews the specific literature on LPG and product tanker shipping market. Based on the review, major literature gaps are identified, namely the lack of coverage for LPG and product tanker shipping market, the inadequacy of current methodologies in tackling shipping freight market relationships, and limited research in spatial pattern analysis. Based on the literature review, specific models are proposed to tackle the research problems, including structural equation modeling, copula model, and discrete choice modeling. Accordingly, econometric analyses of the LPG shipping market are provided. Specifically, the relationship among very large gas carrier (VLGC) market variables, VLGC freight rate dependency with product price arbitrage and oil prices, and VLGC vessel destination choices have been studied. Last but not least, a disaggregate approach has been used to study the freight relationships across major routes for the product tanker market.

This research provides useful guidance for both academics and industrial practitioners on better understanding the freight market dynamics for chartering, asset allocation and diversification purposes. It also fills the gap in the existent shipping literature by analyzing the LPG and product tanker shipping markets, which is of

great importance in the seaborne transportation family, however, received limited research attention.

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CHAPTER 1 INTRODUCTION

Today, crude oil is refined all over the world. However, there is a mismatch of refined products between supply and demand, among and within various regions due to the different numbers of refineries, refinery specifications and outputs, and demand in the region. Therefore, refined products need to be transported by sea to balance supply and demand, which constitutes an important part of the energy supply chain. This thesis aims to provide econometric analyses of product tanker and liquefied petroleum gas (LPG) shipping markets. This chapter provides the background, research objectives, scope and the significance of the study. It also briefly reviews the product tanker and LPG shipping markets, and outlines the research structure.

1.1 Research background

Whereas natural gas and coal could be directly used, crude oil is considered as a complex mixture of different hydrocarbons and generally not consumed in its raw form. Refined petroleum products are derived from crude oil through refining processes such as catalytic cracking and fractional distillation. Refined oil products are incredibly important to today's modern society. Globally, people are dependent on all aspects of petroleum from heating, cooking, transportation, and also industrial uses.

Refined products include: 1) Liquefied petroleum gases (LPG) 2) Gasoline 3) Jet fuel 4) Kerosene 5) Diesel fuel 6) Petrochemical feedstock 7) Lubricating oils and waxes 8) Home heating oil 9) Fuel oil (for power generation, marine fuel, industrial and district heating) 10) Asphalt (for paving and roofing uses). The petroleum products have a variety of usages and different trading patterns. Naphtha is a petrochemical feedstock used by the petrochemical industry. Gasoline can be used as transportation fuel for motor vehicles. Middle East and Europe are the key export regions for naphtha/gasoline, while Asia is the main import region. The US also imports large volume of gasoline every year on the back of strong demand. Kerosene can be used for home and commercial heating and lighting. Asia and Middle East are the main export regions. Africa, Europe and Asia are the main import regions. Jet fuel is light kerosene and can be used for jet aircraft. Asia and Europe are the key export and import regions respectively. Diesel can be used for transport and home heating, industrial furnaces and off-road equipment industry. The US, Russia and Asia are the key export regions, while Europe is the main import region. LPG, the generic name for commercial propane and butane, is a by-product extracted from crude oil refining and natural gas processing. LPG has become an increasingly important energy source for commercial residential fuel, as well as a vital petrochemical feedstock. Middle East and US are the two major export hubs for LPG, with Asia and India being the main importer.

Today, crude oil is refined all over the world. However, there is a mismatch of refined products between supply and demand, among and within various regions due to the different numbers of refineries, refinery specifications and outputs, and demand in the region. Therefore, refined products need to be transported by sea to balance supply and demand, which constitutes an important part of the energy supply chain and a bridge between regions of supply and demand. Global LPG trade increased by around 10% in 2016 to reach 87 million tons (UNCTAD, 2017). LPG can be transported on all types of gas carriers. For long-haul LPG shipping, very large gas carriers (VLGCs) are normally used. Gasoline, jet fuel, kerosene, diesel, and petrochemical feedstock (naphtha) are considered as clean petroleum products and they are carried by coated product tankers. The product tanker shipping market has become an increasingly important part of the seaborne transportation family, yet has received very little research attention, partially due to the complexity of the products carried and diverse trade routes. Research studies on the LPG shipping market are also limited as it is a rather niche market (Adland et al., 2008; Engelen et al., 2011; Engelen and Dullaert, 2010).

Shipping is often held up as the lynchpin of global trade with 80% of the volume of global trade transported by sea. In 2016, total volumes transported by sea stood at 10.3 billion tons (UNCTAD, 2017). Shipping is a derived demand, thus demand for maritime transport services is formed by world economic growth and the requirement to carry merchandised trade. The shipping market exhibits some unique characteristics. Firstly, it is influenced by major random events, such as financial crisis, oil crisis, etc. Secondly, it is a cyclical business with a shipping cycle of eight-year length on average (Stopford, 2009). Thirdly, the capital investment in shipping is high and very often suffer from a time lag of around two years from the ordering to the delivering of a new vessel. Therefore, shipping is a highly volatile and risky industry, where risks and uncertainties are faced by all industry participants.

The freight rate dynamic has been a popular research area due to the uncertainty in international shipping and volatile nature of freight rates. The knowledge of freight rate relationships with various factors and interrelationships would aid shipping practitioners' decision-making process.

This research aims to provide econometric analyses of LPG and product tanker shipping markets. Specifically, it firstly investigates the relationships between freight rates and various market variables, and how the market variables influence vessels' destination choices, with a focus on the VLGC market; and secondly investigate the interrelationship between different freight rates, primarily focusing on product tanker market. The freight market could be influenced by a series of factors, such as aggregated global demand and fleet size (Tinbergen, 1931; Koopmans, 1939; Hawdon, 1978; Beenstock and Vergottis, 1993a). Fleet size is then closely linked to newbuilding and secondhand market. The various relationships have been separately investigated extensively in the bulk shipping market (Hawdon, 1978; Wergeland, 1981; Adland et al., 2006; Kou et al., 2014; Adland and Jia, 2015), however, no study has yet put them into an integrated framework. Failing to do so could result in neglecting important mediating effects among the variables.

Other factors that have an impact on freight rates include location price arbitrage, which has been valued by the industry practitioners (Pirrong, 2014), however, seldom been studied in the academic field. A location price arbitrage is a trading strategy to profit from market inefficiencies in price differences of a given commodity at different geographical locations (Fanelli, 2015). The LPG location arbitrage could affect LPG shipping freight market via two channels: willingness to pay for shipping and ton-mile demand. When the location arbitrage is high, traders will profit more from the price spread and thus have more money to pay for shipowners, which leads to an increase in freight rate. Meanwhile, the open arbitrage would incentivize traders to move more cargoes, which creates more ton-mile demand, and these cargoes need to compete for limited vessel spaces, thus drives up shipping freight rate. On the other hand, when the arbitrage narrows and makes no economic profit to move the cargo, the demand for sea transportation will drop and so will the freight rate. In this study, we examine the dependency between freight rates and commodity price spreads, as price spreads will have a major influence on the arbitrage economics. Freight rates and price spreads together will determine the arbitrage. The oil price effects on freight rates are also of interests but have always been ambiguous and never been investigated thoroughly (Poulakidas and Joutz, 2009).

Calls have been long made in the research community to improve the understanding of spatial patterns in seaborne energy transportation. Technological advances have opened the door to significant innovations in energy shipping behavior modeling, for example, the availability of Automatic Identification System (AIS) data and detailed records of lifting data (including charterer, origin and destination, quantity, ships). Combining the two data sets would enable us to model the spatially disaggregated ship routing behavior at an appropriate scale. AIS data is gaining increasing popularity in the maritime industry as it provides accessible and up-to-date information about vessel activities. AIS, being a shipboard transponder, can transmit vessel information automatically containing vessel identity (IMO, MMSI, name and vessel type), voyage-related information (destination, estimated time of arrival, etc.) and dynamic data (current position including longitude and latitude, speed, and course), among other information (Adland, Jia and Strandenes, 2017). AIS data has been utilized in various fields to tackle different problems, including tracking and security (Ou and Zhu, 2008; McGillivary et al., 2009); maritime risk analysis and prevention, such as collision and oil spill (Eide, 2007; Silveira et al., 2013); environmental issues, such as vessel emissions (Diesch et al., 2013); spatial planning and traffic behaviors (Xiao, et al. 2015; Shelmerdine, 2015); global trade analysis (Adland, Jia and Strandenes, 2017); and vessel speed analysis (Adland et al. 2017; Adland and Jia, 2018). Tu et al. (2018) reviewed the recent research themes using AIS. Shelmerdine (2015) explored the potential use of AIS as a tool to better understand shipping activities by analyzing the information contained in AIS data, which could be used by marine planners and other relevant parties. He highlighted the possible analysis with AIS data including vessel tracking, density maps by use of both vessel tracking and point data, as well as quality control of the data. However, analytical tools, specifically discrete choice models, have not been used in energy shipping studies to examine vessel behaviors and have not been employed to analyze AIS data. Furthermore, most research in the transportation field has focused on transport mode choice or port choice analysis (for example, Malchow and Kanafani 2001; Veldman, et al. 2011). The analysis of ships' destination choice behaviors appears to be an untapped area. This thesis further aims to contribute to this topic by examining how a set of explanatory variables relating to market conditions influence a charterer's behavior regarding destination selection. Understanding the charterer's destination choice is vital in estimating traffic volume to a specific destination and in forecasting supply patterns. It can serve as an indicator of the potential traffic level in the destination ports. It is also critical information for shipowners' planning and vessel deployment decisions. Shipowners can better match their space and cargoes with the knowledge of the charterer's potential destinations. In such circumstances, the question of how a charterer chooses a destination is considered to be an important issue not only for charterers but also for energy transport as well as matching energy demand and supply.

On the other hand, the shipping sector is known to be disaggregated into different segments to carry different cargoes on specific routes. Thus, the freight rates of the different segments typically follow different movements largely driven by the supply and demand balances for different commodities transported (Kavussanos and Visvikis, 2006). However, substitution effects occur between vessels of adjacent size categories (Tsouknidis, 2016), as there are overlaps between cargo transportations in the same or adjacent routes. Substitutions between shipping segments occur when there is a significant difference in freight rates between the segments. Charterer may then choose to divide or combine cargoes, making it possible to take cargoes into another market segment. Owners may also switch trading routes of their vessels for profit maximization purposes. A series of switches between sectors may take place until both markets return to equilibrium. Such substitutions make freight rates of the two vessel sizes or two trading routes interrelated with each other. The trading routes of product shipping market are quite diverse across the global. It is thus of interest to investigate what are the exact dependence structures and extreme co-movements between freight rates of different trading routes and vessel sizes. Such a study is also of benefits for diversification purposes. In today's volatile shipping environment, diversification is vital for shipowners. Diversification could be achieved when a shipowner operates different types of vessels in various sectors, instead of investing only in one sector. Allocating vessels under different trade lanes across the globe could also diversify potential risks. The benefit of diversification is to reduce the risk of loss in expected earnings.

In this thesis, the relationship among VLGC market variables, VLGC freight rate dependency with product price arbitrage and oil prices, VLGC spatial patterns and destination choices, as well as the dependency structure across the product tanker freight market will be studied. This research intends to fill the gaps in the literature by providing an extensive econometric analysis of LPG and product tanker shipping markets.

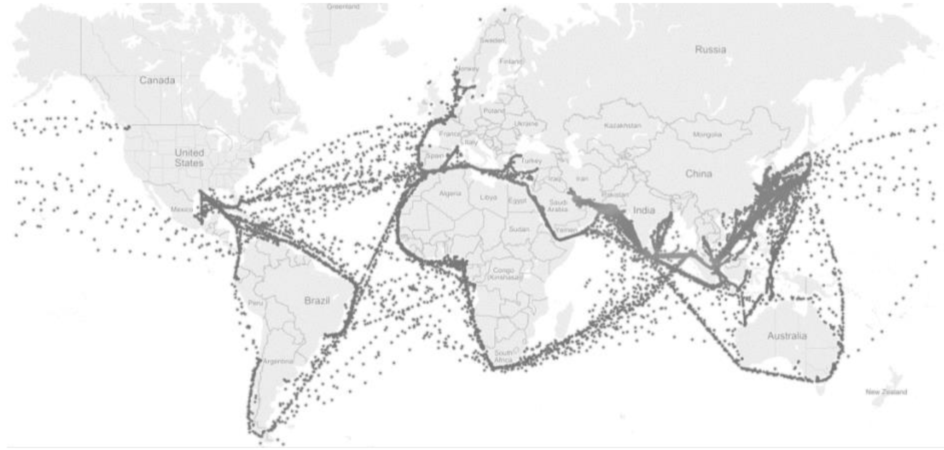
1.2 Overview of LPG and product tanker shipping market

In this section, a general overview of LPG and product tanker shipping markets is provided, including the supply/demand dynamics, main trading routes and freight indexes of the two markets. Specifically, AIS data analysis is performed to identify the trading patterns.

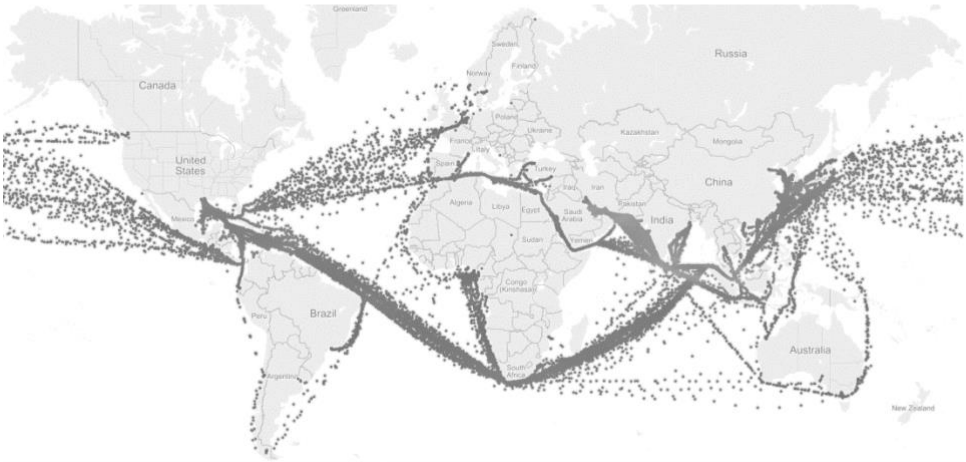
1.2.1 LPG shipping market

In the LPG world, there are two major export hubs, the Middle East and the US. Middle East has traditionally been the largest LPG export region and exported around 37 million tons in 2017. LPG exports from the US have increased significantly in the last few years on the back of the shale gas revolution, from 10 million tons in 2013 to 30 million tons in 2017 (IHS, 2018). The US has shifted from an importer to a net exporter. This trend is likely to continue and the US is set to play a more significant role in the global LPG market. The increase in trade due to US Gulf export is easy to spot on a visual inspection of VLGC activities as shown in Figure 1.1, which illustrates the two VLGC trading pattern density maps in 2012 and 2015 respectively based on AIS data. Imports of LPG into China and India remain firm and lead to raising long-haul trades, which helps to absorb additional LPG carrier capacities as well (UNCTAD, 2017). Another main outlet is Europe. More favorable priced LPG versus naphtha has led to increased consumption of the former and reduction of the latter in the European petrochemical industry.

Figure 1.1 VLGC trading density map



2012



2015

Source: drawn by author based on AIS data.

On the supply side, the VLGC fleet has expanded rapidly in recent years. In Jan 2014, the VLGC fleet consisted of 159 vessels, while in Jan 2018, the number increased to 261 vessels, a massive increase of 64% in just four years.

The benchmark index for LPG freight rate is Baltic LPG index, which tracks the dollar per ton rate for VLGCs loading 44,000mt of LPG from Ras Tanura and discharging in Chiba. LPG freight market is very unique compared to other energy transport markets, such as crude oil and coal. Therefore, it is of importance to investigate separately.

1.2.2 Product tanker shipping market

The main products carried by clean product tankers are naphtha, gasoline, gasoil (diesel) and kerosene. The need for refined product transport arises due to supply/demand imbalances between different regions and product price location arbitrages. Location arbitrages arise when the price at one place is higher than the price at another place plus transportation costs. An open arbitrage window will enable trade flows. Whereas, the most fundamental reasons for trade flows are supply and demand imbalances.

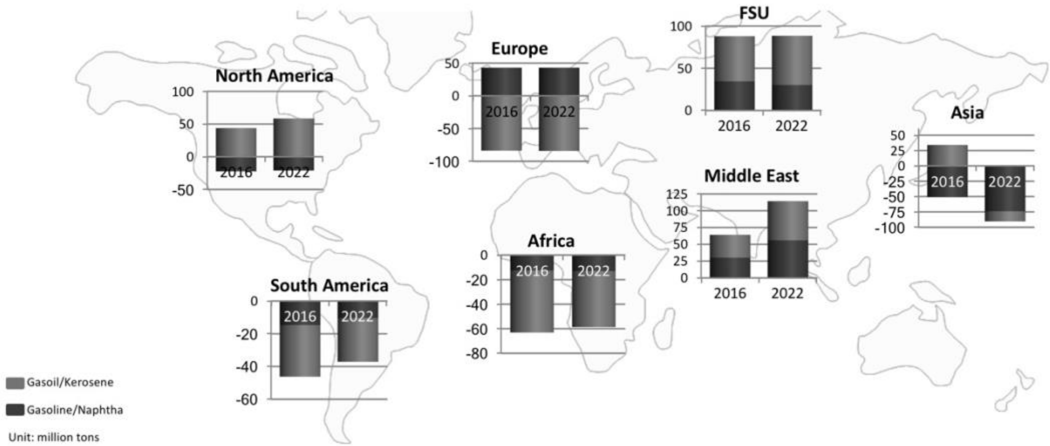
1.2.2.1 Global refined product trade

According to the International Energy Agency (IEA) (2017), as of 2016, Middle East remains the biggest exporter of all refined products in the world. Exports from the Middle East rose sharply in the past few years on the back of new refineries in the region. Middle East exports totaled 43.7 million tons of naphtha in 2017, up from 41.1 million tons in 2016. The main importer is Asia. Asia imported around 56 million tons of naphtha on Long Range One (LR1) and Long Range Two (LR2) in 2017. Less attractive pricing of rival feedstock LPG, higher cracker operating rates, and strong gasoline demand were some of the reasons.

Europe is long in gasoline/naphtha and short in distillates, including gasoil and kerosene. Supply of naphtha in Europe increased as a result of new refineries in Russia. Europe exported around 12 million tons of naphtha in 2017, up 16% compared to 2016 levels. Some of the naphtha was exported to Asia. On the other hand, Europe needs to import gasoil and kerosene from the East. Total gasoil/ultra-low Sulphur diesel exports from the East to the West were 21.2 million tons, representing an annual decrease of 22% in 2017. This is due to the fact that bloated inventories and increased throughput in Europe incentivized buyers to source barrels locally or draw down stocks. High levels of refinery maintenance turnarounds in Asia also negatively affected the flow. Outflows from the Middle East totaled 18.3 million tons, down from the record level in 2016 at 21 million tons. The largest outlet for Middle Eastern cargoes, Europe, which accounted for 90% of the volumes, imported 16.5 million tons in 2017. Jet fuel exports to West were around 16.6 million tons, down 4% compared to previous year. It was a fall in Middle East exports that dragged down the performance as Far East exports rose during the same period.

The US imports a large volume of gasoline every year on the back of strong demand. This figure was around 26.5 million tons in 2017. Meanwhile, US distillates export is on an increasing trend. In 2017, the US exported 27% of total domestic distillate production. Around 68 million tons of distillates were exported, half of which went to South America and around 30% went to Europe. Figure 1.2 shows the global refined product imbalances.

Figure 1.2 Global refined product imbalances flow



Source: drawn by author based on IEA (2017).

It should be noted that developments in refinery capacities have significant impacts on shaping crude and product trade patterns. For example, the decline of refining capacity in Europe, Japan and Australia, and an increase in the Middle East and Asia have changed clean tanker geography to a large extent, and this may also lead to increased volatility in freight rates. For one instance, the Middle East has begun to shift from crude oil exports to developments in the downstream such as refineries, leading to more refined product exports (UNCTAD, 2015).

1.2.2.2 Product tanker fleet

Three main size categories for product tankers are Medium Range (MR) tankers (35,000 – 59,999 dwt), Long Range One (LR1) tankers (60,000 – 79,999 dwt) and Long Range Two (LR2) tankers (80,000 – 119,000 dwt). There are also handysize tankers (25,000 – 34, 999) engaging in regional refined product trades. However, these vessels are primarily designed and employed for chemical trades. Nowadays, there are Long Range Three (LR3) vessels in the water, but the number is quite limited. The size of LR3 is equivalent to Suezmax tankers in the dirty tanker market. LR2 is equivalent to Aframax and LR1 equivalent to Panamax. The main difference between clean carriers and dirty carriers is that clean carriers are normally coated (such as epoxy) in order to carry refined products. However, sometimes, clean carriers could switch to carry crude oil when the dirty market is booming, which could justify the switch-over and cleaning-up costs.

Table 1.1 Product tanker fleet summary (as of Jan 2018)

	LR2	LR1	MR
Existing fleet	348	356	1498
Ships trading clean	206	232	
Orderbook	46	28	163
Average age (years)	8.1	9.6	9.8

Source: compiled by author based on Lloyd's List (2018).

As shown in Table 1.1, the existing fleet of LR2, LR1 and MR as of January 2018 are 348, 356 and 1498 respectively. The orderbook for LR2 is quite heavy, which is 13% of the existing fleet. The net LR1 fleet expansion has been minimal since 2012. The average growth from 2012 to 2017 is 4%. Following brisk ordering activities a couple of years ago, 106 MRs entered the water in 2015, implying a net fleet expansion of 9%, the highest one since 2010.

1.2.2.3 Main product tanker trading routes

The East of Suez has traditionally been the main trading area for the LR2s. Exports from the Middle East to Asia has long been an established route. However, the surge of naphtha exports from Europe to Asia in recent years has attracted some units to the western hemisphere, as can be seen in Figure 1.3.

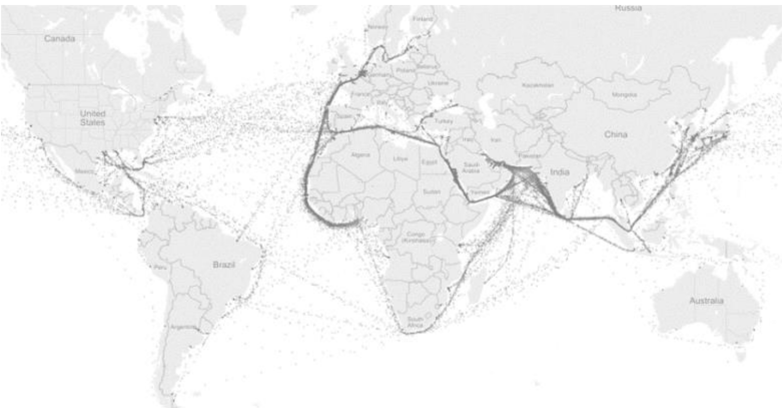
The Middle East to Asia is also the main trading route for LR1s. However, West Africa's imports of refined products from Europe have become an increasingly important market for the LR1s.

MRs are more flexible and versatile than LR1s and LR2s. From the density map for MRs (as shown in Figure 1.5), it can be seen that trading routes are more complex and spread all over the world.

Figure 1.3 Density map of LR2 trading clean in 2015

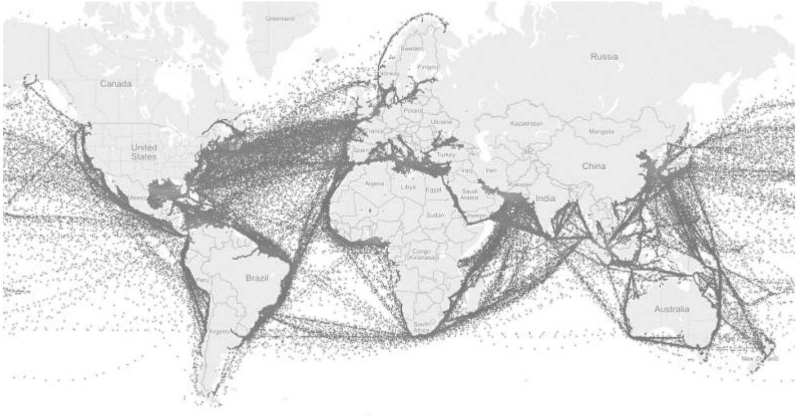
Source: drawn by author based on AIS data.

Figure 1.4 Density map of LR1 trading clean in 2015



Source: drawn by author based on AIS data.

Figure 1.5 Density map of MR trading clean in 2015



Source: drawn by author based on AIS data.

1.3 Research objectives

Based on the above-mentioned research background, the primary objective of this research is to provide econometric analyses of the LPG and product tanker shipping markets. As such, the following detailed objectives are outlined and shall be achieved in the thesis, including:

1) To examine the relationships between the key market variables (supply/demand, freight rates, and secondhand and newbuilding prices) in the VLGC market in an integrated approach;

2) To investigate the dependency between VLGC freight rates and product price arbitrage and oil prices;

3) To study the spatial patterns of the VLGC market and examining how a set of explanatory variables relating to market conditions influence a charterer's behavior regarding destination choices.

4) To examine the dependency structure and extreme co-movements across various product tanker routes;

1.4 Research scope

This research concentrates on the LPG and product tanker shipping freight markets. The main focus of the research is on freight rates, including their interrelationships and relationships with other variables. LPG can be lifted on all types of LPG carriers, from VLGCs to pressurized ships. VLGCs predominately lift long-haul volumes. For LPG export from the Middle East and the US, we normally use VLGCs. In this research, VLGC shipping market is analyzed as a representative of LPG shipping due to the large volume of LPG that VLGCs carry and their dominant market share in LPG shipping. An aggregated approach is taken for the VLGC shipping market as there is well-established benchmark route (from Ras Tanura to Japan) and freight index, which is known as Baltic LPG index (BLPG) and tracks the dollar per ton rate from Ras Tanura to Japan. This study first investigates the relationships between the key market variables to have a holistic view of the VLGC market. The variables include market pressure (a ratio of ton-mile demand over ton-mile supply), freight rate, new building and secondhand vessel prices. The study then takes a further step by investigating the relationship between freight rate and product price arbitrage and oil prices, apart from the supply and demand factors analyzed in the first step. Furthermore, the research aims to discover the spatial patterns of the VLGC market and investigate VLGC vessels' destination choices based on a set of explanatory variables. For the product tanker market, as there are many different routes and vessel sizes, it is impossible to analyze in an aggregated manner as the VLGC market. Therefore, it may not be feasible to study the relationships among key market variables for product tankers as a whole, instead, to study the freight rate relationships across different product shipping routes would have more practical significances, such as for diversification purposes.

1.5 Research significance

1.5.1 Academic significance

This research provides academic significances in the following ways. Firstly, it fills the gap in the existent shipping literature by analyzing the LPG and product tanker shipping markets, which is of great importance in the seaborne transportation family, however, received limited research attention. The econometric analysis of the two shipping markets provides insights into the LPG freight formation process and dynamics, and the dependency structure between different product tanker freight rates. Secondly, this study takes a novel perspective in investigating the freight rate formation, which relates the freight rate development to the spatial arbitrage, which has been appreciated by industry practitioners, but little investigated by the academy. This study also makes methodological advancements by introducing time-varying copula approaches in the shipping domain. The copula methods provide more flexibility and accuracy in freight relationship and dependency modeling. Furthermore, this research is one of the first to model vessels' destination choice behaviors and identify their associations with various market factors. Last but not least, the application of AIS data in analyzing shipping trade and spatial patterns is another novel contribution made by this study.

1.5.2 Practical significance

The findings of this thesis are beneficial for shipping practitioners by providing decision tools as well as practical implications. Studying the various relationships may have direct implications for shipowners and related agents in the shipping sector, such as charterers and asset players. This study could help shipowners combine anticipated changes in freight rate and vessel prices with information concerning demand and supply changes, thus make more informed decisions regarding lending, ordering, and purchasing of vessels. In addition, by knowing the development of crude oil price and the arbitrage economics, the industrial practitioners would also have a clearer view of the market movements. Furthermore, understanding the dependency between freight rates on different trading routes will aid shipowners' decision-making process about vessel allocations in different trading routes for diversification and risk mitigation purposes. Last but not least, this work draws significant implications for transportation planning. Understanding a charterer's choice of destinations is vital in determining traffic volume to a specific destination and also in forecasting future vessel supply patterns.

1.6 Thesis structure

This report will consist of 6 chapters as follows.

Chapter 1 provides the background, objectives, scope, significance, and structure of this research.

Chapter 2 conducts the literature review focusing on the different aspects of tramp shipping freight market, identifying the major trends and methods in each topic. The existing research is classified into four categories, namely supply-demand modeling, freight rate process modeling, freight rate forecasting and freight rate relationships. The study also reviews the specific literature on LPG and product tanker shipping markets. Based on the review, major literature gaps are identified.

Chapter 3 presents the research process flow and methodologies to be used in the next chapters. It introduces Structural Equation Modeling (SEM), copula-GARCH model and discrete choice modeling in the shipping domain.

Chapter 4 investigates the LPG shipping market in three ways. Firstly, SEM model is applied to analyze interrelationships between supply/demand, freight rates, and newbuilding and secondhand prices in an integrated framework. Secondly, copula-GARCH model is employed to study the time-varying dependency between LPG freight rate, product location arbitrage and crude oil prices. Thirdly, a discrete choice model is proposed for VLGC destination choice analysis for cargoes originated from the US Gulf and its relationship with several explanatory attributes is identified, including the freight rate, commodity price arbitrage, bunker price and the number of ships in a specific area.

Chapter 5 examines dependencies and extreme co-movements across six major clean product tanker shipping freight rates by the copula-GARCH model.

Chapter 6 summarises this research's major findings and contributions. Limitations of this study and recommendations for future research are also provided.

CHAPTER 2 LITERATURE REVIEW

This chapter reviews past literature on freight rate modeling in the bulk shipping market, identifying the major themes and methodologies. The objective of this chapter is to review academic research on physical freight market in bulk shipping using quantitative methods. This chapter adopts a systematic review approach to identify major trends and themes in the bulk shipping freight market and pinpoints gaps in the literature.

2.1 Background

Due to its importance to world trade, maritime transportation research has attracted much research attention. Recent review studies have attempted to identify the broad research areas, specific topics and methodologies employed (Davarzani et al., 2016; Lee et al., 2016; Notteboom et al., 2013; Shi and Li, 2017; Talley, 2013; Woo et al., 2011, 2012, 2013; Alexandridis et al., 2018). Talley (2013) classified the literature into 'shipping' and 'port' research, and further divided them into 19 sub-categories. For shipping-related literature, he included seafarers, short sea shipping, shipping finance, freight rates, shipping performance/management and shipping safety. Shi and Li (2017) identified three research areas including 'shipping', 'port' and 'maritime fleet'. Woo et al. (2011, 2012, 2013) and Notteboom et al. (2013)'s review work focused specifically on seaport research. Davarzani et al. (2016) and Lee et al. (2016) mainly discussed environmental themes associated with ports, maritime logistics, and transportation. Alexandridis et al. (2018)'s work examined shipping finance and investment related research. These review papers have studied the general themes and tools used in the broad maritime transport research. Freight rates, although mentioned as a research sub-category (Talley, 2013), have not been investigated extensively. Davarzani et al. (2016) and Lee et al. (2016) mainly discussed environmental themes associated with ports, maritime logistics, and transportation. However, as it is known, due to the uncertainty in international shipping and volatile nature of freight rates, the freight rate dynamic has become an important and popular research area. Glen (2006) provided a survey on the modeling of dry bulk and tanker markets. However, such review was done in the last decade and consequently, methodological advancements in recent years have not been captured. Alexandridis et al. (2018) reviewed research work on volatility and spillover effects in the freight market as part of risk measurement and management in shipping topics. However, it is only a sub-section of the review article and does not elaborate on the methodologies and trends in this area. Thus, a systemic review of freight market research is necessary to identify freight characteristics, behaviors, as well as general topics and methods used in freight study.

2.2 Literature review approach

The systematic review aims to provide joint insights into certain fields and to enhance methodological rigor. The systematic review could also help establish a sound knowledge base for practitioners by collecting information from a wide range of previous research (Tranfield et al. 2003). Potential research gaps shall be identified to highlight knowledge boundaries, which could serve as a reference point for future research. This section describes the literature review approach and summarizes major bibliometric statistics.

2.2.1 Description

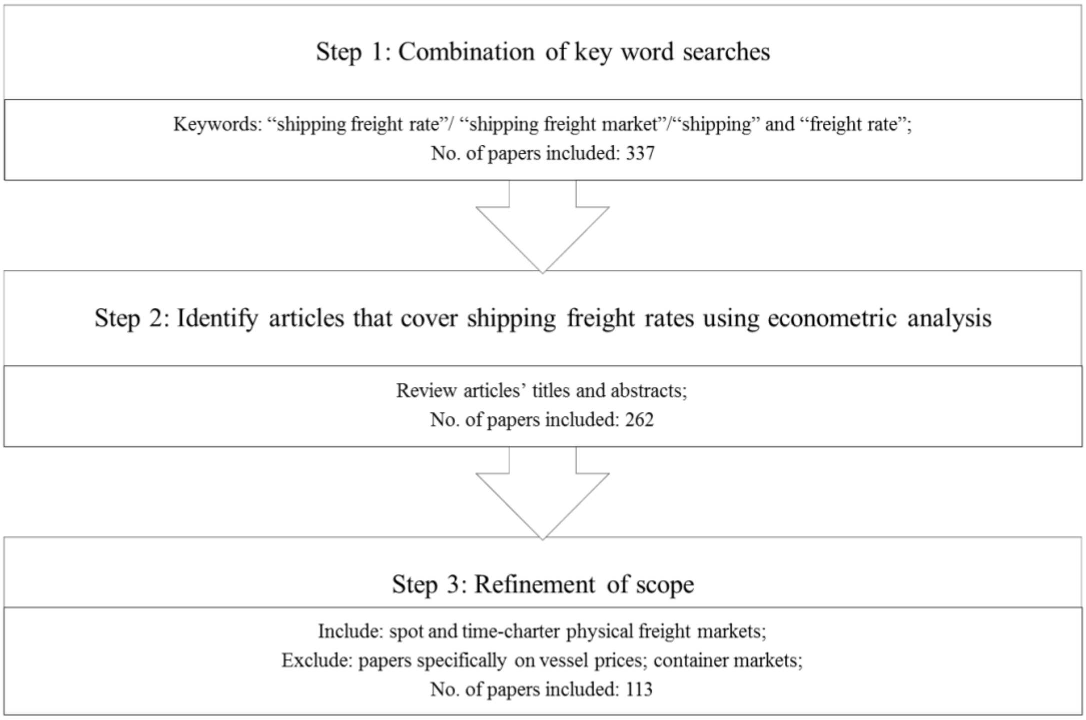
In this thesis, freight rate studies in bulk shipping published in academic journals are included. In this paper, freight rate studies in bulk shipping published in academic journals are included. Important seminar papers and book chapters in the early years are also included, as they provide the major source of knowledge at that time. Journal papers have a more solid theoretical basis, concepts and models, thus, should be considered as the primary source of literature review (Rowley and Slack, 2004). Furthermore, journal papers have gone through peer review procedures and are considered more rigorous and appropriate for both theoretical and methodological investigation. The time span under investigation is from the 1930s when the pioneer econometric analysis for bulk shipping market was published (Tinbergen, 1931) to 2017.

To identify all relevant literature, the following steps are performed. Firstly, the combination of keyword searches which include “shipping freight rate”/ “shipping freight market” are performed in Scopus, Web of Science, ScienceDirect and Google Scholars for all peer-reviewed journals. Any articles that contain the keywords in title, abstract or keywords are selected. The initial result returns 337 papers. Secondly, each article’s title and abstract were reviewed first to identify the major topics covered. After review, we reserved the articles that cover shipping freight rates using quantitative analysis. 262 articles were selected for further examination and the rest were removed as they were not relevant to our study.

In the final step, the selected 262 articles were investigated thoroughly and the scope was further refined with the following criteria. Firstly, the scope of analysis is limited to current spot and time charter rates, which represent the physical freight market. Papers on freight derivatives markets alone are not covered in this paper. Secondly, we also exclude papers specifically focusing on vessel prices, as the main focus of this study is the freight market. Thirdly, the container market is also excluded as the main focus is on bulk shipping market. Container shipping and bulk shipping markets follow rather different mechanisms and dynamics, thus reference drawn from the container market analysis may not be suitable for bulk shipping markets. Last but not least, additional important articles frequently cited and appeared in the reference, but not in our database using keyword search are also included.

Using such criteria, 113 papers remain as our final articles under review. A database was used to record all necessary information about each paper, including authors, publication year, journal, the objective of the study, methodology, key findings and limitations. The database was updated constantly for comparison and future analysis. Figure 2.1 below illustrates the entire article filtering process.

Figure 2.1 Paper selection process



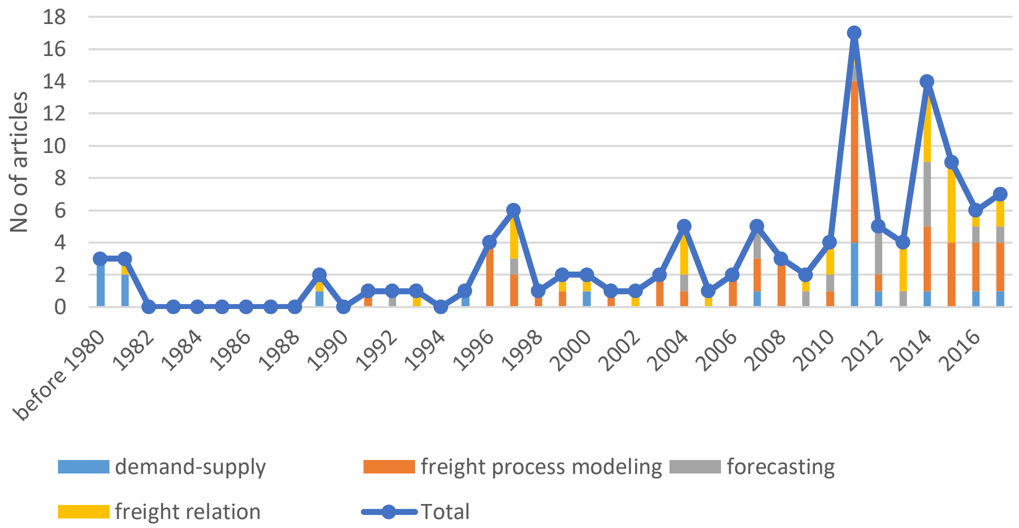
2.2.2 Bibliometric statistics

The literature database indicates that the 113 articles are published in 41 journals. *Maritime Policy & Management* and *Maritime Economics and Logistics* are the top two publishing journals, followed by *Journal of Transport Economics and Policy* and *Transportation Research Part E*, which are the major journals for transportation and maritime-related issues. Economics journals such as *Applied Economics* and *Energy Economics* also appear in the top of the list, as freight rate analysis often contains modern econometric techniques. Table 2.1 records the top host journals and number of papers contributed to each journal. The top 10 journals include around 70% of total 113 articles reviewed. Figure 2.2 shows the number of publications per year to generate publication trend. The number of publications in different research categories is indicated in different colored bars, while the dotted line shows the total number of publications in a given year. The different research themes are further illustrated in details in Section 2.3. As can be seen, shipping freight rate studies have emerged in as early as the 1930s, however, received limited attention before 1989. Earlier studies have mostly focused on building full-scale supply-demand models. Modeling the freight rate process has come into the spotlight in the 1990s and since then becomes a popular research area. Forecasting for bulk shipping freight rates appears to be a relatively new research area and the total numbers on this subject are limited (18 articles out of 113). Potentially due to the complex nature and high volatility of the shipping market, it seems difficult to obtain a certain level of accuracy for freight rate forecasting. For the same reason, volatility has become a popular research topic and is grouped under freight rate process modeling.

Table 2.1 Top host journals and number of papers published

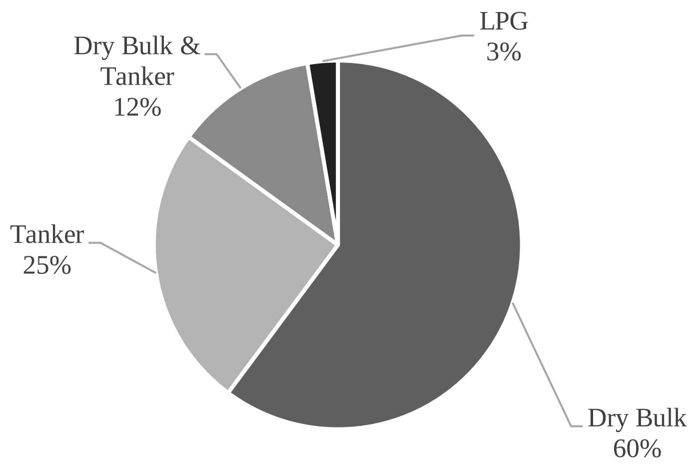
Journal	No. of articles
Maritime Policy & Management	22
Maritime Economics and Logistics	19
Transportation Research Part E: Logistics and Transportation Review	10
Journal of Transport Economics and Policy	8
Applied Economics	5
Asian Journal of Shipping and Logistics	4
Energy Economics	3
Transportation Research Part A: Policy and Practice	3
International Journal of Transport Economics	3
Others	36
Total	113

Figure 2.2 Publications per year on bulk shipping freight rates



The publications are further broken down according to the shipping sectors covered as shown in Figure 2.3, it is notable that dry bulk accounts for 60% (68 articles) of final shipping freight literature identified (113 articles) in this study and tanker sector constitutes another 25% (28 articles). LPG shipping market has only been studied in three papers due to its niche market nature. Furthermore, most literature identified in tanker shipping focus on crude oil tankers. For product tanker market, Baltic Clean Tanker Index (BCTI) or individual routes have been separately studied to a limited extent (Alizadeh et al., 2015; Kavusanos and Dimitrakopoulos, 2011). Some scholars also jointly investigate tanker and dry bulk shipping markets to identify similarities and differences in terms of freight behaviors (Veenstra, 1999), or to identify the relationship of the two markets and combined carrier effects (Beenstock and Vergottis, 1993). It is also noted that most research attention has been given to the larger vessel size segments, for example, Capesize and Panamax in the dry bulk market and VLCC in the tanker market.

Figure 2.3 Market sectors covered in bulk shipping freight literature



Source: Author.

2.3 Research themes in freight rate modeling

Econometric techniques are gaining more and more popularity in recent years among researchers to analyze freight rate behaviors. The quantitative literature on freight rates can be classified into four categories as listed in Table 2.2. The first category is to model freight rates through a supply-demand framework, namely, a structural approach is adopted to model freight rates and other determinant variables in linear regression systems. The second theme is to model the freight rate dynamics itself, including freight characteristics and volatility. Stationarity test has been extensively used. The structure of freight autoregressive nature has been studied. Furthermore, freight rate forecasting has been another research scheme. Different techniques such as time series analysis and artificial intelligence have been explored by researchers. Last but not least, scholars are also interested in freight rate relationships, which include:

i) The term structure between spot and period rates (Glen et al., 1981; Hale and Vanags, 1989; Wright, 2000; Kavussanos and Alizadeh, 2002);

ii) The relationship between spot and forward rates (Kavussanos and Visvikis, 2004; Li et al., 2014);

iii) Freight interrelationships and spillover effects between different size categories and different markets (Veenstra and Franses, 1997; Wright, 1999; Tsouknidis, 2016);

iv) Freight rate dynamics with newbuilding, secondhand and scrapping market (Dai el al., 2015; Kou and Luo, 2015);

v) Freight rate relationship with commodity prices. Apart from the relationships mentioned above, some studies also investigate freight rate dynamics with oil prices, or the price of the commodity which the vessel carries (Alizadeh and Nomikos, 2004; Poulakidas and Joutz, 2009; Shi et al., 2013).

Table 2.2 Main research themes, topics and the number of articles identified in the literature

Main research theme	Sub-topics	No. of articles
Model freight rates through a supply-demand framework	Macro approach; Micro approach	17
Model freight rate dynamics itself	Freight characteristics; Stationarity; Volatility; Seasonality	46
Freight rate forecasting	Supply-demand modeling; Stochastic modeling; Artificial intelligence techniques	18
Freight rate relationships	Term structure between spot and period rates; Relationship between spot and forward rates; Interrelationships and spillover effects between different size categories and different markets; Relationship with newbuilding, secondhand and scrapping market; Relationship with commodity prices	35

The 113 identified articles contain 17 papers on supply-demand modeling, 46 on freight process modeling, 18 on forecasting and 35 on freight relationship. There may be publications covering more than one research theme.

2.3.1 Supply/Demand model

Some early quantitative analysis of shipping freight rates appeared in the 1930s. Most studies at this time mainly adopt a structural approach, namely to model freight rates and other determinant variables in linear regression systems (Beenstock and Vergottis, 1989a, 1989b, 1993; Hawdon, 1978). Tinbergen (1931) and Koopmans (1939) conducted the pioneering studies. Tinbergen (1931) establishes the first quantitative analysis of shipbuilding and freight markets. In the earliest time, more efforts have been spent on modeling the supply side of the freight market and less attention given to the demand side. This is mainly due to the more complicated nature of the demand side. Later on, more emphasis has been given to investigate the supply and demand dynamics.

The major quantitative models used in freight markets are summarized below. Tinbergen (1934) conducted pioneer research using econometric models in shipping and identified the changes in demand and supply variables on freight rates. The factors include bunker prices and fleet size, to name a few. His study included data from 1870 to 1913. In his work, demand function is perfectly inelastic while the supply function is fairly inelastic. Koopman (1939) studied the tanker freight rate determinants by a supply and demand model, which is one of the earliest econometric applications and one of the first few to point out the peculiar shape of the supply curve in the tanker market. The author concluded that the supply curve is steep or inelastic in the case of full fleet employment, while under a partial employment condition, the supply curve tends to be flat or elastic. This implies that when fleet utilization is low, a demand change would not change freight rates to a large degree, but when existing fleet utilization is high, increase in transportation demand will have a large effect on rates. Hawdon (1978) regressed freight rates against a set of independent variables, such as demand per unit of capacity, newbuilding prices, average ship size, bunker prices from 1950 to 1973. The results show that tanker freight rates could be significantly influenced by demand per unit and fuel prices, while the statistical relationships for the rest variables were found to be insignificant.

Earlier quantitative models focused mostly on modeling the supply side, while the demand side was often neglected by researchers. Norman (1979) for the first time investigated the relationship between demand for shipping and OECD countries' Gross National Product (GNP) indicators. He concluded that such indicators could to a large extent explain the shipping demand changes. Following Tinbergen (1934)'s work in modeling supply side, Wergeland (1981) further studied freight rates in a supply-demand framework. The demand is modeled as a ton-mile function with independent variables: global trade (positive relationship) and freight rates (negative relationship). His findings were in line with Tinbergen (1934)'s that freight rates are inelastic to supply and demand changes, with supply being less inelastic. Beenstock and Vergottis (1989a, 1989b) conducted a series of work and established integrated econometric models for both dry bulk and tanker markets. In their models, freight rates are expressed as a function of demand (in ton-miles and being exogenous), supply (active fleet) and bunker prices.

Traditional freight rate formations as mentioned above are often investigated at the macro level using aggregate demand or supply factors. On the other hand, a separate strand of literature has investigated the freight rate formation at the micro level using spot fixture data (Adland et al., 2016; Adland et al., 2017; Alizadeh and Talley, 2011a; Alizadeh and Talley, 2011b; Agnolucci et al., 2014; Köhn and Thanopoulou, 2011; Tamvakis and Thanopoulou, 2000). Such an approach could account for heterogeneity with respect to vessel technical and contract specifications (Adland et al., 2016). For example, Alizadeh and Talley (2011a, 2011b) investigated tanker and dry bulk spot freight rates using vessel- and contract-specific determinants, as well as macro market variables. Adland et al. (2016) employed fixed effect regression techniques to study the characteristics of charterers and owners and use them as microeconomic determinants of freight level.

2.3.2 Freight rate process modeling

Beenstock and Vergottis (1993)'s work serves as a high watermark in the application of traditional econometric models, as mentioned by Glen (2006). Since Beenstock and Vergottis (1993), shipping research has shifted into a new direction. More studies have abandoned structural models and focused on modern econometric techniques, such as univariate time series analysis to investigate the statistical properties of freight rates and the structure of their autoregressive nature (Kavussanos, 1996; Kavussanos and Alizadeh, 2002; Jing et al., 2008). Structural models have their own drawbacks as they typically require a large number of variables and some of them could be difficult to assess (such as vessel utilization). On the other hand, the efficient market hypothesis in the shipping market has justified the modeling of freight rate itself in a time series model. If the market is efficient, freight rates are supposed to encompass all information that is publicly available and there would be no extra variables needed except for freight rates for the model building process (Evans, 1994; Veenstra and Franses, 1997).

2.3.2.1 Stationarity, freight rate properties, and seasonality

Under the trend of using modern econometric techniques instead of building large-scale structural models, more and more researchers have begun to put emphasis on econometric measures to model freight rate dynamics and explore statistical properties of freight rates. Unit root analysis is performed by many researchers (Adland and Cullinane, 2006; Tvedt, 2003; Veenstra and Franses, 1997; Koekebakker et al., 2006) to test the stationarity of freight rates. The stationarity of data is often a prerequisite for most of the techniques applied to the modelling of freight rates. The general consensus is that freight rates are non-stationary in level form, but stationary in first-order difference. Tvedt (2003) is an exception. He claimed that the reason for non-rejection of non-stationarity in the literature is that freight rates are dominated in USD. If freight rates are transformed to Japanese Yen (as argued by the author that Japan and the rest of Asia play a more significant role than North America in the dry bulk market), freight rates seem to be stationary. Unlike most work that based on linear ADF test, Koekebakker et al. (2006) applied a unit root test against a non-linear stationary alternative and found that all bulk freight rates are stationary. However, this method has not been followed by many researchers. Table 2.3 summaries major stationarity tests and their respective results from the literature. The results indicate that most researchers have reached the conclusion of non-stationarity for freight rates. Apart from that, freight rates also exhibit time-varying, non-linear and non-normal characteristics as a general consensus (Adland and Cullinane, 2006; Adland et al., 2008; Goulielmos, 2009; Kavussanos, 1996; Kavussanos and Alizadeh, 2002; Tvedt, 2003; Xu et al., 2011). The auto-correlated nature of freight rates has also been studied. For example, Cullinane (1992) conducted a time series analysis and forecasting by the Box-Jenkins method. He got an ARIMA (3, 1, 0) model due to data limitations.

Seasonal behavior is another area of interest. Stopford (2009) argued that dry bulk freight rates exhibit seasonal behavior owing to the commodities periodically transported. Kavussanos and Alizadeh (2001) found evidence of seasonal behaviors of freight rates in both dry bulk and tanker rates. Poblacion (2015) studied the seasonal behavior of tanker freight dynamics employing a four-factor model and found that stochastic seasonality models perform better than deterministic seasonality models.

Table 2.3 Overview of results from stationarity tests in previous literature

Author(s)	**Purpose**	**Data**	**Data period**	**Frequency**	**Test(s)**	**Conclusion**
Veenstra and Franses (1997)	Freight rate forecasting using cointegration	Capesize/Panamax routes	1983-1993	monthly	ADF	Non-stationary[1]
Glen and Martin (1998)	Tanker market risks difference for different size vessel and term structure	Tanker spot and time charter index	1973-1996	monthly	ADF, PP	Non-stationary
Veenstra (1999)	The term structure of freight rates	Drybulk TCE and spot rates	1980-1993	monthly	ADF	Non-stationary[2]
Wright (2000)	Spot and time charter rates' long run parity	Tanker freight indices	1982-1996	monthly	DF, ADF	Non-stationary
Kavussanos and Alizadeh (2001)	Seasonality in spot and time charter rates	Drybulk TCE and spot rates	1980-1996	monthly	Seasonal unit root	Non-stationary
Kavussanos and Alizadeh (2002)	The expectation hypothesis of the term structure	Drybulk spot and time charter rates	1980-1997	monthly	ADF, PP	Non-stationary
Tvedt (2003)	Stationarity of freight rates	Drybulk TCE and spot rates	1988-1999	weekly	ADF	Stationary[3]
Haigh et al. (2004)	Freight rates integration and causality	Individual BPI routes	1996-2001	daily	ADF	Non-stationary[4]
Kavussanos and Visvikis (2004)	Lead-lag relationship in returns and volatilities	Drybulk spot and FFA rates	1997-2000	daily	ADF, PP, KPSS	Non-stationary
Alizadeh and Nomikos (2004)	Relationship between oil price and tanker freight	Tanker spot rate	1993-2001	weekly	ADF, PP, KPSS	Non-stationary
Koekebakker et al. (2006)	Stationarity of freight rates	Drybulk and tanker TCE	1990-2005	weekly	Non-linear unit root	Non-linear stationary
Adland et al. (2008)	Spot freight dynamics in Liquid Petroleum Gas transport	LPG TCE	1992-2005	weekly	ADF, PP, KPSS	Stationary

Note: ADF is the augmented Dickey and Fuller test for stationarity. The null hypothesis is the series has a unit root. PP test is Phillips and Perron test for stationarity. The null hypothesis is the series has a unit root. KPSS test is proposed by Kwiatkowski et al. (1992) against the null hypothesis of stationarity. The seasonal unit root test is established by Beaulieu and Miron (1993). Koekebakker et al (2006) adopted a non-linear unit root test proposed by Kapetanios et al. (2003). 1) Two panamax route stationary at 5% level. 2) One spot series stationary at 5% level. 3) Non-stationary when freight rates denoted in USD, stationary when converted to JPY. 4) One route stationary at 5%.

Source: adapted from Koekebakker et al. (2006).

2.3.2.2 Freight rate volatility modeling

Freight rate volatility has been another main research strand, due to the highly volatile nature of shipping freight market. In the past years, a substantive number of approaches utilizing ARCH (Autoregressive Conditional Heteroscedasticity and GARCH (Generalized Autoregressive Conditional Heteroscedasticity) models have emerged (Kavussanos, 1996; Glen and Martin, 1998; Chen and Wang, 2004; Jing et al., 2008; Alizadeh and Nomikos, 2011). Such models discard the standard econometric assumption of constant variance of error terms. These models have been adopted by many researchers to examine the time-varying volatility of freight rates. Freight volatility refers to the variability or the dispersion of freight rates. Engle (1982) first developed the model and later Bollerslev (1986) further extended it. These models allow both the conditional mean and variance of the data series to be modeled simultaneously. This allows the variance to change over time. Kavussanos (1996) for the first time applied ARCH and GARCH models in the shipping industry to analyze the time-varying behavior in dry bulk freight rates of different sizes, as well as aggregated spot and time charter rates. His model included the conditional mean, variance, and density of the error term in the regression equation. The results pointed out that ARCH and GARCH parameters are significant and the model provides a better fit compared with the classical linear model. Following Kavussanos's efforts, Glen and Martin (1998) applied similar techniques in the tanker market and examined the conditional volatility of vessels of different sizes and between different types of period charter. Kavussanos (2003) investigated risks in the tanker freight market utilizing GARCH model and unveiled that time charter rates are generally less volatile than spot rates, while freight rates of larger ships have higher volatility than smaller ones.

Later researchers have extended GARCH model to various forms, including Exponential-GARCH (EGARCH) and GARCH-X (Kavussanos and Alizadeh, 2002; Chen and Wang, 2004; Jing et al., 2008; Alizadeh and Nomikos, 2011; Drobetz et al., 2012). Table 2.4 shows the major application of GARCH models in bulk shipping freight literature. The table indicates that from the original GARCH model, researchers have begun to compare different GARCH forms and attempted to find the best-fitted ones. More recently, some studies have also extended it to multivariate forms (Xu et al., 2011). Exponential GARCH could model the conditional variance as an asymmetric function of past innovation, thus being capable of capturing inverse relationships between current returns and future volatilities (Chen and Wang, 2004; Jing et al., 2008). Chen and Wang (2004) studied the leverage effect in bulk shipping markets by EGARCH. Jing et al. (2008) concluded that volatility in different period charters and different vessel sizes responses to market shocks of different magnitude in the dry bulk market. The authors divided the samples into two periods to investigate different asymmetric impacts during two sub-periods. Alizadeh and Nomikos (2011) pointed out that the shape of the term structure could affect the volatility and this relationship is asymmetric. They compared different GARCH models and conducted out of sample forecast for both dry bulk and tanker markets, using both time charter and spot rates in different sub-sectors. The conclusion is that EGARCH-X outperforms in most cases and stands out in terms of forecasting performance. Drobetz et al. (2012) studied the effects of shocks from macroeconomic variables and asymmetric effects on volatility in dry bulk and tanker markets using GARCH-X, EGARCH, and EGARCH-X models. They used Daily Baltic Exchange indices in the period of 1999 to 2011. In their study, they specifically allowed for a *t*-distribution rather than only a normal distribution to better depict the fat tails of error terms and concluded that a *t*-distribution is more suitable than a normal distribution. They further pointed out the existence of strong asymmetric effects in the tanker market and non-existence of such effect in the dry bulk market.

As a short summary, research studies have evolved from the original GARCH models to different GARCH specifications and extensions to capture flexibly different volatility behaviors. The distribution of error terms has also been considered by recent studies. The standard normal distribution has been re-examined by some scholars and efforts have been made to use t-distribution to account the fat-tailed behavior of freight rates.

Univariate GARCH models have one major limitation: they only model the conditional variance of independent series, thus, being univariate in nature. As a result, any 'volatility spillovers' between different markets cannot be modeled. Furthermore, in the financial market, the covariance between the series is as important as the variances of individual series. Some studies have also extended univariate GARCH models to multivariate forms (Kavussanos and Visvikis, 2004; Xu et al., 2011). Kavussanos and Visvikis (2004) applied VECM-GARCH-X model to examine the volatility spillover effect between spot and FFA prices. Xu et al. (2011) studied the relationship between freight rate volatility and the growth in fleet sizes, bunker prices among other variables in the dry bulk shipping markets using the GARCH model and GMM regression.

However, such model is still based on the linear framework and not able to capture the non-linear relationships between the series.

Table 2.4 Applications of GARCH models in bulk shipping freight literature

Author	Sector	Time period	Methodology	Purpose	Main finding
Kavussanos (1996a)	Dry Bulk	1973-1992	GARCH	To analyze the freight rate time-varying behavior for different size categories and spot and time charter rates in the dry bulk market	ARCH and GARCH parameters are significant and the GARCH model fits better compared to the classical linear model
Kavussanos (1996b)	Tanker	1973-1992	ARIMA-X and GARCH	To analyze the monthly tanker price volatility for different size vessels	Oil price increase impacts negatively on aggregated tanker prices and positively on volatility
Glen and Martin (1998)	Tanker	1973-1996	GARCH	To estimate the conditional volatility between different sizes and types of period charter for tankers	The larger tankers are riskier than smaller vessels, and time charter rates are less volatile than spot rates
Kavussanos and Alizadeh (2002)	Dry Bulk	1980-1997	EGARCH-M	To investigate the expectations hypothesis in time charter rate formation of the term structure	Result does not support the expectation hypothesis of the term structure of the period 1980-1997
Chen and Wang (2004)	Dry Bulk	1999-2003	E-GARCH	To examine the leverage effect on volatility in the bulk market	1) Market downturns have more significant leverage effects compared to market upturns; 2) Leverage effects are more significant for larger vessels than smaller ones.
Jing et al. (2008)	Dry Bulk	1999-2005	GARCH/E-GARCH	To investigate freight rate volatility characteristics for three different bulkers	Volatility in different vessel sizes and different period charters responds to market shocks in different magnitudes
Alizadeh and Nomikos (2011)	Dry Bulk and Tanker	1992-2007	Augmented E-GARCH	To identify the relationship between term structure and freight rate volatility, compare the predicting performance of various GARCH models	Freight rate volatility is related to the term structure shape of the freight market.
Koseo and Barut (2011)	Dry Bulk and Tanker	2002-2008	Co-integration, Granger causality, GARCH	To measure market earnings volatility and its spillover effects between the tanker and the dry bulk shipping	Tanker earnings more volatile than the dry bulk market; a long-term relationship between the two markets and unidirectional mean spillover effect from dry to tanker market
Xu et al. (2011)	Dry Bulk	1973-2010	AR-GARCH and GMM regression	To investigate the determinants of freight rate volatility (including fleet size, bunker, demand)	Changes in fleet size have positive impacts on freight rate volatility
Drobetz et al. (2012)	Dry Bulk and Tanker	1999-2011	compare GARCH-X, EGARCH, and EGARCH-X	To study whether macroeconomic shocks or asymmetric effects could contribute to the explanation of time-varying volatility in the dry bulk and tanker market	1) a t-distribution is more suitable than normal distribution for error term; 2) Macroeconomic factors should be modeled into the conditional variance equation instead of the conditional mean equation; 3) Strong asymmetric effect in the tanker market, but no such effect in dry bulk

2.3.2.3 Other freight rate process modeling techniques

Many researchers have proposed some stochastic modeling methods apart from a time series analysis to characterize freight rate dynamics, both by parametric and non-parametric models adopted from financial economics. For parametric models, the Geometric Brownian Motion (Tvedt, 1997) and the Ornstein–Uhlenbeck process (Jørgensen & De Giovanni, 2010; Kou and Luo, 2015) have been frequently used. Non-parametric models are fully functional procedures. Instead of imposing a specific parametric structure, they identify the functions describing the solution to the stochastic differential equation (Tvedt, 2003; Adland and Cullinane, 2006; Adland and Strandenes, 2007). Adland and Cullinane (2006) modeled the spot freight rate process as a non-parametric Markov diffusion model and found that freight rates follow a traditional mean-reverting process in the long run, but has a unit root in the short run. However, because of high volatilities in spot freight rates, the model has a limitation in terms of detecting slow-speed mean reversion in high-frequency data. Adland et al. (2008) investigated the freight dynamics in the LPG carriers for the first time using similar techniques and concluded that a simple linear stochastic model can approximately describe LPG freight rates and the rates do not show the non-linearity which is found in other bulk shipping segments.

One drawback of the stochastic freight rate models is that they neglect all the information not contained in the current spot rates and past innovations. Therefore, some important information may not be taken into account.

Fractal analysis techniques using non-parametric specifications also receive some researchers' attention. Engelen et al. (2011) adopted multifractal detrended fluctuation analysis (MF-DFA) and rescaled range analysis to examine freight characteristics of VLGCs and found that VLGC freight rates demonstrate limited time-dependent persistence with controlled volatility and trend-reinforcement. However, the study was done in 2011, when the VLGC market has limited trading patterns and much smaller fleet size compared to 2016, which results in controlled volatility as the authors argued. Goulielmos and Psifia (2011) used a rescaled range analysis and concluded that dry bulk index in the period of 1971 to 2005 is not normally distributed and have fat-tails.

2.3.3 Freight rate forecasting

Shipping is often perceived as a market of being highly volatile and unpredictable, which is largely due to its derived nature of global trade. Coupled with shipping market unique characteristics, such as speculative behaviors, time lags between the time of ordering and delivering of vessels, shipping freight rates exhibit high volatility. Freight rates thus, at first sight, may seem to follow a random walk and hard to predict due to such effects (Engelen et al., 2011). To facilitate more accurate forecasting, more research in the literature has shifted from building large-scale econometric or simulation models to more direct specifications of freight rate process itself or reduced forms (Glen, 2006). As such, the statistical properties could be obtained. Appropriate forecasting techniques could enable players in the shipping business to make better and informed decisions. Broadly speaking, there are three commonly used techniques for freight rate forecasting, namely supply-demand modeling, stochastic modeling and artificial intelligenice techniques.

2.3.3.1 Supply-demand modeling

Traditional full-scale supply-demand model as discussed in Section 2.3.1 could be used for forecasting. To this end, new-building prices, second-hand prices and demolition prices and fleet development are often included as independent variables to predict freight rates (Chang et al., 2012). Randers and Goluke (2007) described the shipping market as a “4-year” cycle superimposed on a “20-year” wave, in addition to lots of noise. The first cycle is the capacity utilization adjustment loop, which is the consequence of ship owners’ short-term behavior given the current market conditions, such as slow steaming or lay-up, the latter one being the capacity adjustment loop, which refers to the ship owners’ tendency to order too many ships in a booming market. However, full-scale supply-demand models are often more robust for longer time forecasting, say around 1-4 years. For a shorter-time horizon, the forecast may not be feasible due to significant noise (Randers and Goluke, 2007).

2.3.3.2 Stochastic modeling

Stochastic modeling refers to the probability theory in the phenomenon modeling in technologies and natural sciences. Famous models include time series models such as Autoregressive Integrated Moving Average (ARIMA) model, Vector Autoregressive (VAR) model and Vector Error Correction (VECM) model. There is plenty of research done in both bulk and tanker market utilizing stochastic modeling techniques. For example, Cullinane (1992) for the first time employed a Box-Jenkins approach to forecasting the Baltic International Freight Futures Exchange Speculation in the short term. Such an approach has revolved around and is known as the ARIMA model. Veenstra & Franses (1997) identified the freight rate process to be non-stationary and used a VAR model to forecast dry bulk freight rates. The model does not perform well in the longer term. The authors concluded that freight rates are stochastic in nature and thus cannot be forecasted. The limitation of the VAR model is that the the long-term forecasts of the VAR model tend to converge to the mean of the series. Batchelor et al. (2007) investigated the forecasting accuracy in the spot and forward rates of some popular time series models on major trading routes and concluded that the vector error correction model (VECM) could fit the sample best, but the prediction power, in reality, is poor. They further concluded that ARIMA and VAR models perform better for forecasting forward rates. The potential benefit of the bivariate VAR model compared to the univariate ARIMA model is that the information contained in the movement of spot freight rates can be used to determine forward rates and vice versa. As a short conclusion, shipping freight rates exhibit complex characteristics, including non-linearity and non-stationary, which makes it difficult for traditional stochastic modeling techniques to strike a balance between accuracy in forecasting and the model's theoretical feasibility. The forecasting accuracy for most time series models examined in previous studies are often unsatisfactory.

2.3.3.3 Artificial intelligence techniques

A newly emerged area is artificial intelligence techniques based on statistical learning theory (Li and Parsons, 1997; Lyridis et al., 2004; Fan et al., 2013; Han et al., 2014). Such methods have a good fitting ability for complex nonlinear function (Han et al., 2014). Compared to supply-demand models and stochastic models, more explanatory variables can be fed into Artificial Intelligence AI) models to achieve a higher forecasting accuracy. AI models can flexibly account for non-linear autocorrelations and cross-correlations with independent variables. Li and Parsons (1997) were first to use Artificial Neural Network (ANN) to forecast Mediterranean freight rates of the crude oil tankers using data from 1980 to 1995 and three variables including spot freight rates, the total capacity of active tankers and the Drewry's tanker demand index are considered. They developed two ANN models for freight rate forecasting, the first one utilizing only freight rate self-correlation information, while the second one making use of all information from the three variables. To make result comparisons, they also established two parallel autoregressive moving average (ARMA) models and the results show that ANN models outperform ARMA models in all cases. Later on, scholars attempted to incorporate more explanatory variables. Lyridis et al. (2004) implemented an ANN in the VLCC market to forecast Ras Tanura-Rotterdam spot freight. Eleven variables are identified as input, including demand for oil transportation, active fleet, newbuilding and secondhand prices, etc. Apart from ANN models, other AI models have also been explored. For example, Han et al. (2014) adopted wavelet transformation to denoise BDI data series and support vector machine (SVM) to forecast the index. They further compared the results from the SVM model against VAR, ARIMA and neural network methods and concluded that SVM better performs in forecasting.

Limitations of Artificial Intelligence models exist. They are often regarded as a black-box method as the causal relations cannot be detected and no formal test could be done. For a pure forecasting purpose, AI models are often preferred for higher out-of-sample predicting accuracy. However, they may not be suitable when statistical relationships need to be identified.

2.3.4 Freight market relationships

As mentioned earlier, freight rate relationships include the following five categories: 1) Term structure; 2) Spot and forward freight relationship; 3) Freight interrelationships (which includes relationship between different sub-sectors and across different sectors); 4) Freight rate relationships with newbuilding, secondhand vessel prices; 5) Freight relationships with commodity prices, include oil prices, prices of commodities the vessel carries, etc. The following subsections will cover the major literature in each category, highlighting trends and gaps.

2.3.4.1 Term structure between spot and period rates

There is a wide range of contractual arrangements in shipping markets, including spot and time charter contracts. Time charter contracts are the contracts under which a charterer takes control of the operational aspects of the ship and pays to a shipowner a fixed monthly amount. On the other hand, in spot markets, a shipowner takes the operational control of the ship and a charterer will look for a ship when a cargo transportation is needed. The payment is normally made on a voyage basis. The existence of different contractual types attracts researchers to look at the relationship between spot and period rates. The well-perceived assumption that shipping market is purely competitive with rational and efficient agents was pushed further by the term structure relationship between spot and period freight rates and the theoretical framework pointed out by Zannetos (1964). Zannetos (1964) pointed out that static expectations in tanker demand and supply essentially infer a future freight level that is the same as current rates. Thus, before any changes in present prices occur, future rates under static conditions could be developed from objective data. Glen et al. (1981) developed a continuous time model to study the relationship between time charter and spot rates and operating costs. They used quarterly data from 1970 to 1977 of individual tanker fixtures. They applied the model to test the Zannetos (1964)' elastic price expectation hypothesis and concluded that shipowners are risk-averse, which is in the resonance of Strandenes (1984)'s findings. Hale and Vanags (1989) assumed rational expectation and market efficiency to test the term structure hypothesis. They established a formal relationship between the time charter rates and the expected spot rates. They used data for the period 1980-1986 in the dry bulk sector and found the coefficient on the spread between the lagged value of spot equivalent period rates and the spot rates that prevailed is negative and insignificant for two ship sizes out of three. However, Veenstra (1999) pointed out that these results suffer from "omitted variable" biases and the results are significantly different after correcting this error. Kavussanos and Alizadeh (2002) explained the failure of expectations hypothesis of the term structure due to the existence of time-varying risk premiums. On a separate note, Alizadeh and Nomikos (2011) found that freight rate volatility has a relationship with the term structure shape of freight markets. Such a relationship is found to be asymmetric. Volatility tends to be higher in a market of backwardation than a market of contagion.

2.3.4.2 Spot and forward freight relationship

Shipping spot and derivatives market are found to be highly related (Kavussanos and Nomikos, 2003; Kavussanos and Visvikis, 2004; Li et al. 2014). In fact, the emergence of shipping derivatives can be attributed to high volatility found in the spot market which urges shipowners and charterers to find an instrument to hedge freight rate risk. Kavussanos and Nomikos (2003) examined the casual relationship between spot and future prices and found that new information tends to be discovered by futures prices first. Kavussanos and Visvikis (2004) investigated the lead-lag relationship between spot and FFA price in daily returns and volatilities in the dry bulk market. They used cointegration test and VECM-GARCH-X model to examine the spillover effects both in returns and volatilities. They identified the non-storable nature of the underlying commodity (shipping service) and concluded that a bi-directional lead-lag relationship exists in the means, which is in line with most financial futures markets. Li et al. (2014) further explored such relationship in the tanker market using multivariate GARCH models. They found a unilateral spillover effect in returns from one-month FFA to spot markets and a bilateral effect in volatilities between the two markets.

2.3.4.3 Freight Interrelationship

The interdependency and spillover effects between freight rates of different vessel sizes and different market segments have also been investigated by several scholars. One of the common techniques used for interdependency study is

Johansen (1988)'s cointegration test (Wright, 1999) and vector autoregressive models (Veenstra and Franses, 1997). Veenstra and Franses (1997) tested the long-run relationship between six major dry bulk shipping routes using a vector error correction model (VECM) and found that freight rates of the six routes are closely linked and tend to co-move in the long run. Wright (1999) examined the tanker market integration by investigating the relationship between freight rates (both spot rates and time charter rates) of different vessel sizes. His finding suggested that there exists a high level of integration in the tanker market.

Recently, multivariate GARCH models have been employed to study the volatility spillover effects. Chen et al. (2010) studied the lead-lag relationship between Capesize and Panamax freight rates by a bivariate ECM-GARCH model for four shipping routes from 1999 to 2008. Chung and Weon (2013) further investigated the asymmetric spillover effects between Panamax and Capesize markets by bivariate asymmetric mixed normal GARCH models. Skewdness and Kurtosis of the return distributions are accounted for in the model. They identified significant spillover effects, especially for the direction from larger-size to smaller-size vessels. Volatility spillover effects between and within tanker and dry bulk freight market have been studied by Tsouknidis (2016) by a multivariate DCC-GARCH model. The results suggested that there exist time-varying volatility spillovers among different shipping markets, particularly since 2008 where a financial crisis occurred. More recently, Adland et al. (2018) developed a continuous stochastic model for the joint dynamics of regional bulk spot rates and found that regional spot freight rates can be decomposed into two parts: a stationary regional differential and a non-stationary market component. The market component can be interpreted by a global market average. This allows for easier interpretation of regional differences for freight rates.

Markets for combined carriers have also been analyzed (Beenstock and Vergottis, 1993). Beenstock and Vergottis (1993) studied the spillover effects between dry bulk and tanker markets through the combined carrier market, shipbuilding and scrapping markets. They concluded that increasing dry bulk freight rates would attract combined carriers from the tanker market. Furthermore, more dry bulk carriers are expected to be built at shipyards, which eventually leads to tanker price increase.

2.3.4.4 Relationship between freight rates and vessel prices

Freight rate dynamics with vessel prices also received some researchers' attention. The methodologies employed are diverse in this subfield. Strandenes (1984) introduced the present value model of ships in the shipping economics and studied the relationship between second-hand vessel prices and time charter rates. Based on the efficient market hypothesis, the value of a second-hand ship should be entirely explained by the present value of short run and long run profits. Kavussanos and Alizadeh (2002) rejected the efficient market hypothesis of the newbuilding and secondhand vessel prices in the dry bulk market and attribute the failure to the existence of time-varying risk premium. Such relationship was modeled by a GARCH in the mean (GARCH-M) model. Lunde (2002) extended the net present value criteria in a continuous time model to study the freight rates – vessel price relationship. Error correction models have also been employed to study the relationship between freight rates, newbuilding and secondhand vessel prices (Tsolakis et al., 2003; Adland et al., 2006). Tsolakis et al. (2003) found that secondhand vessel prices are driven by time charter rates and newbuilding prices, while Adland et al. (2006) identified the cointegration relationship between secondhand prices and both newbuilding and freight markets. By cointegration test, Alizadeh and Nomikos (2007) further concluded that secondhand vessel prices and freight rates in the dry bulk shipping are co-integrated and information transmits from the latter to the former. The relationship between newbuilding vessel price and freight rates in the dry bulk market has been studied by Xu et al. (2011). Kou and Luo (2015) took the effects of structural changes into consideration and examined the relationship between freight rates and vessel prices. The freight rate process is modeled as an Ornstein–Uhlenbeck process. They also concluded that prices of newer and larger vessels are more sensitive to changes in freight rates, which are in line with Kavussanos (1996a, 1996b)'s results.

2.3.4.5 Relationship between freight rates and commodity prices

More recently, researchers have attempted to model the relationship between shipping freight rates and the prices of the underlying commodities which the vessels carry. The rationale behind is the derived nature of maritime transportation. Thus, it is reasonable to assume that there exist volatility spillover effects between commodity prices and freight rates. For tankers, such commodity could be crude oil, and for dry bulkers, iron ore, grain, to name just a few, could be relevant.

There has been a body of research devoted to the analysis of the freight rate–crude oil relationship. Alizadeh and Nomikos (2004) investigated the causal relationship between crude oil tanker freight rates and crude oil prices (WTI, UK Brent, and Nigerian Bonny). They identified a long-run relationship between the freight rate and oil price in the US, using a vector error correction model. They found no evidence supporting that the physical-future crude oil price differentials relate to the freight rate formation. Hummels (2007) concluded that the sensitivity of freight rates to changes in oil prices is very high. Poulakidas and Joutz (2009) investigated the lead-lag relationship between tanker freight rates and the oil price by conducting cointegration and Granger causality analysis. They further pointed out that the relationship between spot tanker freight rates and crude oil prices could be ambiguous, which is caused by different forces of supply and demand. As addressed by Glen and Martin (2005), if the oil price increase is due to a rise in oil demand, the relationship between spot tanker freight rates and crude oil prices shall be positive due to an increase in demand for oil transportation; on the other hand, such a relationship would become negative if the increase in oil prices is attributed to the cut in oil supply, which reduces the demand for oil transportation. UNCTAD (2010) published an empirical study on the effects of oil prices on shipping freight rates for containers, iron ore and crude oil; and the findings revealed that the elasticity of freight rates to oil prices differs a lot across different market segments and conditions. The elasticity for iron ore is found to be larger than that for crude oil and container, while the effect of oil prices on container freight is higher during sharp rising or increased volatility in oil prices. Shi et al. (2013) investigated the contemporaneous relationship between tanker freight rates and crude oil prices using a structural vector autoregressive model. They further classified crude oil price shocks into supply shock and non-supply shock and concluded that supply shocks have a significant impact on the tanker market, while non-supply shocks do not. Sun et al. (2014) explored the dynamic relationship between oil prices and tanker freight rates by multiscale relevance techniques and identified different relevance structures in low and high oil price environments. Gavriilidis et al. (2018) found that incorporating oil price shocks improve volatility forecasts for tanker freight rates using GARCH-X models.

With respect to the dependency between freight rates and commodity prices, Kavussanos et al. (2014) for the first time investigated the return and volatility spillover between the freight rate and derivatives of commodity prices the vessel carries in the dry bulk market using BEKK-VECM GARCH model. They concluded that new information normally first appears in the returns and volatilities of the commodities' futures markets before spilled over into the freight futures market.

As a short conclusion, researchers have studied extensively the freight relationships in terms of term structure and spot-forward rates. The relationship with vessel prices and the freight spillover effects have also been identified. The freight rate and commodity price relationship appears to be an emerging and ongoing research theme.

2.3.4.6 General methodologies for dependence modeling in shipping literature

As a summary of the methodologies employed in the literature, cointegration test and VAR model (VECM as one restricted form) are the most common techniques for freight relationship analysis (as shown in Table 2.5). The table further lists out the key trends, pros and cons for each method. Early researches extensively use cointegration test for long-run relationship analysis. Cointegration tests normally adopt the Engle-Granger two-step test (Engle and Granger, 1987) or the Johansen cointegration method (Johansen, 1988, 1991). To better understand the causal relationship, the Granger causality test has been employed (Poulakidas and Joutz, 2009; Koseo and Barut, 2011). Starting from Veenstra (1999) and Kavussanos and Nomikos (1999, 2000), Vector autoregression (VAR) and Vector Error Correction Model (VECM) have become a popular tool for joint behavior analysis. More recently, scholars have extended GARCH modeling to multi-dimensional cases and adopted Multivariate GARCH in shipping literature to examine volatility spillover effects. Kavussanos et al. (2014) identified the relationship between dry freight rates and commodity prices in a BEKK VECM-GARCH model. However, the common methodologies used can only pinpoint whether a long-run relationship exists and the possible directions of information flow. The exact dependency structure has seldom been investigated. Although the VAR and multivariate GARCH model sheds lights on possible dependency structure, however, it is based on linear framework and incapable of capturing the complex non-linear relationships that many freight series may exhibit. The following section lists out the common methodologies and their brief definitions.

Table 2.5 Methodologies for freight dependency modeling in shipping literature

<table>
<tr><th>Methodology</th><th>Literature</th><th>Key trends; Pros & Cons</th></tr>
<tr><td>Cointegration Test</td><td>Berg-Andreassen (1997); Wright (1999); Wright (2000);
Koseo and Barut (2011)</td><td><u>Trends</u>: Extensively used in earlier studies.
<u>Pros</u>:
Able to test the existence of a long run equilibrium relationship;
Ease of use.
<u>Cons</u>:
Sensitivity to lag selection;
Engle-Granger method: Unable to identify more than one cointegrating relationship and impossible to validly test hypotheses about the cointegrating vector.
Johansen method: Tend to signal cointegration where non exists.</td></tr>
<tr><td>Granger Causality</td><td>Poulakidas and Joutz (2009); Koseo and Barut (2011)</td><td><u>Trends</u>: Not used as a single method in literature, often coupled with other techniques.
<u>Pros</u>:
Identify possible direction of influence.
<u>Cons</u>:
Strict assumption needed;
Designed to handle two variables, may provide misleading results for three or more variables.</td></tr>
<tr><td>Vector Autoregression (VAR) and Error Correction</td><td>Veenstra (1999); Veenstra and Franses (1997); Alizadeh and Nomikos (2004); Chen et al. (2010); Shi et al. (2013)</td><td><u>Trends</u>: More constraints imposed on the parameters of traditional Error Correction models for parsimony concerns.
<u>Pros</u>:
Able to capture the linear dependency among a number of series;
Simple equation and estimation, usual OLS method can be used;
No need to determine endogenous vs exogenous variables, all variables in the equation are exogenous.
<u>Cons</u>:
Difficult to transform data if some of the variables are stationary and some are not;
The multidimensional VAR model uses many degrees of freedom.</td></tr>
<tr><td>Multivariate GARCH (MGARCH)</td><td>Chung and Weon (2013); Kavussanos et al. (2014); Li et al. (2014); Dai el al. (2015)</td><td><u>Trends</u>: Examination of different MGARCH specifications to allow for different covariance structures.
<u>Pros</u>:
Able to estimate co-volatility dynamics of asset returns in a portfolio.
<u>Cons</u>:
Relatively more complex estimation process;
Difficult to strike a balance between model flexibility and parsimony;
The covariance matrix, by definition, needs to be positive definite.</td></tr>
</table>

Cointegration test, developed by Engle and Granger (1987) and Johansen (1988) is used to test the long-run relationship between variables. If two series are co-integrated, shocks to the system will eventually return the system to equilibrium. Let two series be integrated of order 1. In general, a linear combination of the two series, say$(y_t - bx_t) = \varepsilon_t$, will be integrated of order 1. In the special case when ε_t is integrated of order zero, the two series is said to be co-integrated.

Granger Causality, introduced by Granger (1969), could be used to identify the direction of possible causality between the two variables. Formally speaking, Granger causality tests whether past values of x could assist in the prediction of y_t, under the condition of having already considered the effects on y_t of past values of y (and probably of past values of other variables). If so, then x is said to "Granger cause" y. The null hypothesis implies that past values of x have no predictive content for y_t.

Vector Autoregression (VAR) model was proposed by Sims (1980) and has become popular in econometrics as a natural generalization of univariate autoregressive models and a technique to describe the joint dynamic behavior of a set of variables. A VAR structure has a set of n variables and each variable can be stated as a linear function of past p lags of the variable itself and p lags of all of the rest $n - 1$ variables, as well as an error term. VAR models are flexible and easy to generalize. They are often considered as an alternative way to large-scale simultaneous equations structural models. A vector error-correction (VEC) model is used, when the variables of a VAR are co-integrated.

Multivariate GARCH models specify the covariance structure between series, apart from many similarities as univariate GARCH models. Several different multivariate Different multivariate GARCH formulations have been used in past literature, and the one appeared in shipping research is BEKK model proposed by Engle and Kroner (1995), for example, Li et al. (2014). Such a model could describe volatility spillovers between different price series and is often used together with a VAR model which could capture the mean spillover effects.

2.3.4.7 Copula method for dependence modeling

As pointed out by Jondeau and Rockinger (2006), it is not possible to identify a multivariate extension to capture the dependence structure for most kinds of univariate distributions. In this study, we will propose a novel methodology in maritime economics to study the dependency structure in a GARCH context, which is based on copula functions. Our copula-GARCH model nests a traditional GARCH model as a special case. The advantages of copula-based GARCH models over traditional multivariate GARCH models are that they can be applied to link together any type of marginal distributions that are proposed for the individual series. On the other hand, different dependence structures could link the same marginal distributions into different joint distributions (Lee and Long, 2009).

The word Copula appeared for the first time in 1959 (Sklar, 1959). Schweizer and Wolff (1981) published the earliest paper which relates copulas to dependence study among random variables. However, the application of copula concept is rather a modern phenomenon. Nelsen (1999) provided an introduction to copula theory, while Cherubini et al. (2004) discussed the copula methods for financial applications. A lot of literature exists on the use of copulas for the computation of Value-at-Risk (VAR) in risk management (Cherubini and Luciano, 2001), the dependence of stock market returns (Sun et al., 2008) and portfolio management (Patton, 2004; Riccetti, 2013). Copula method has also found its application in actuarial science, such as to model dependent mortality and losses (Frees et al, 1996; Frees and Wang 2005). In biomedical studies, copulas are used to model correlated event times and competing risks (Wang and Wells, 2000).

Copula method compared to traditional multivariate time series analysis has several advantages. Copula-based models provide more flexibility in modeling multivariate distributions, allowing researchers to specify the models for the marginal distributions separately from the dependence structure that combines them to form a joint distribution. The copula approach to formulating multivariate distributions is particularly beneficial when the marginals are complex and cannot simply extend to a multivariate situation (Liu and Luger, 2009).

Recent literature has used copulas which provide a more complete description of the dependency structure. Copula functions go beyond common elliptical models such as the multivariate normal or multivariate t distributions (Embrechts et al., 2002). In this context, many researchers have employed copula-GARCH models, where a univariate GARCH process is used to model the marginals and a copula function is then specified to model the dependence structure. Copula-GARCH models have been found in several financial time series analyses (Dias and Embrechts, 2004; Patton, 2006; Hu, 2006; Jondeau and Rockinger, 2006; Rodriguez, 2007; Liu and Luger, 2009). Hu (2006) focused on mixed copula modeling of dependence among financial variables, with the parameters estimated using semi-parametric procedures applied to the residuals in GARCH models fitted to data. Aloui et al. (2013) studied the co-movement between oil prices and exchange rate utilizing copula-GARCH model. The dependency between daily returns of major stock markets has also been extensively studied using similar approaches (Jondeau and Rockinger, 2006; Liu and Luger, 2009). Lee and Long (2009) further considered the extensions and empirical applications of multivariate GARCH models with copula-based specifications of dependence among the vectors. Recently, a number of researches have extended the copula model with time-varying dependency structure. Patton (2006) introduced copulas with time-varying parameters to model exchange rate dependence, including Japanese yen and Euro against US dollars. He proposed that the current dependence structure between two series could be described by their previous dependence and the cumulative probabilities' historical average difference. Jondeau and Rockinger (2006) modeled the daily return market in the copula-based GARCH framework with the skewed Student-t error distribution, by a Markov-switching time-varying dependency model. Wu et al. (2012) also adopted the copula-GARCH model to study the co-movement between oil prices and exchange rates, with time-varying dependence parameters. Empirical evidence has shown that the dependency among many financial returns is time-varying (Jondeau and Rockinger, 2006).

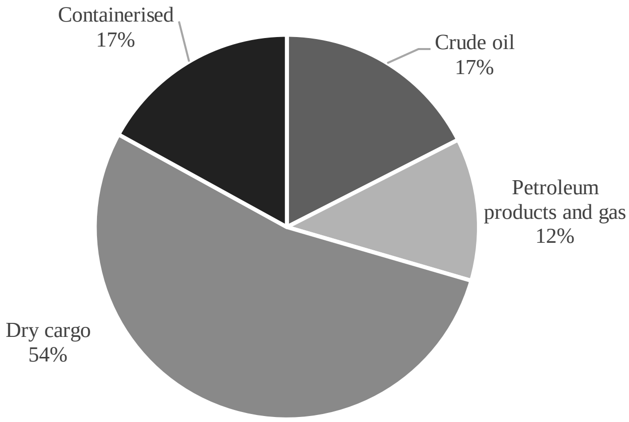
However, such method is almost untapped in the shipping academic research. Only very recently, Shi et al (2016) adopted time-varying copula models in the freight derivatives market. Modeling the dependency between different shipping rates is a difficult task when the rates follow very complicated dynamics. As mentioned earlier, Goulielmos and Psifia (2007) concluded that trip and time charter indices exhibit nonlinear dependence structure. As a consequence, linear and other traditional models are not suitable for modeling freight distributions. They further concluded that the indices are not normal, but instead show skewness, kurtosis, fat tails and long-term memory.

In the next chapter, we will briefly review the main definitions concerning copulas and describe the different copula functions used in the empirical application.

2.4 Review on LPG and product tanker shipping market

According to UNCTAD (2017), of the total seaborne trade, crude oil accounts for around 17%, while petroleum products and gas for roughly 12% as shown in Figure 2.4. Despite the growing importance of gas as a cleaner energy source and increasing volume of global LPG trade, research on LPG transport has been limited, as discussed in Section 2.2.2. This might be due to the limited size of the market in the past. However, it is of vital importance to understand the freight behavior in these two markets for decision making.

Figure 2.4 Structure of international seaborne trade, 2016



Source: drawn by author based on UNCTAD (2017).

Most literature employs non-parametric methodologies for spot freight analysis. Adland et al. (2008) investigated for the first time, the price dynamics of the LPG transport market. They adopted fully functional methods and concluded that unlike other bulk shipping markets where non-linearity is found, LPG spot freight rate could be described approximately by a simple linear stochastic model. As discussed by them, the LPG market is uniquely supply driven rather than demand driven, as the LPG volume is dependent upon the extraction rate of LNG and crude oil, and therefore is not independently set. Another unique feature of LPG shipping is that the market may not be perfectly competitive due to high levels of concentration both on the supply and demand side. On the supply side, VLGCs are owned by a handful number of owners, while the oil majors and gas producing companies constitute the demand side. Furthermore, Main trading routes for LPG transport are limited, which creates more price volatility as the sensitivity to market conditions tends to increase, compared to other shipping markets with diversified trading patterns and cargo bases (Adland et al., 2008). Last but not least, Majorities of LPG transport volume between main exporters in the Arabian Gulf and Far East importers, are performed under term contracts, leaving small volume traded on spot basis. This leads to more demand volatility. The demand for spot cargo would be influenced by product price arbitrage, freight rates, supply disruptions or surplus. On the other hand, due to the by-product nature of

LPG, there often exists energy substitutes such as naphtha, which could also be used as a petrochemical feedstock same as LPG. Thus, demand for LPG shipping becomes more elastic and this, in turn, lowers freight rate volatilities.

Engelen et al. (2011) further investigated VLGC spot rates by multifractal detrended fluctuation analysis (MF-DFA) and rescaled range (R/S) analysis. Both methods are non-parametric. Additionally, Engelen and Dullaert (2010) investigated the market structure and efficiency in gas shipping in more details. They identified the demand/supply features in LPG, ammonia, and petrochemical shipping markets. For product tanker market, Baltic Clean Tanker Index (BCTI) or individual routes have been separately studied to a limited extent (Kavusanos and Dimitrakopoulos, 2011; Alizadeh et al., 2015).

2.5 Summary of major literature gaps

The transportation of refined petroleum products is of great importance to energy supply chains across the globe. However, as mentioned in Section 2.2.2, most literature in tramp shipping freight focus on dry bulk and crude oil tankers. LPG and product tanker markets have been an almost untapped area in the academic field. To the best of authors' knowledge, only three studies have been done so far in the LPG freight market, and almost no study yet in the product shipping market. For the LPG shipping market, existing literature mainly focuses on analyzing the freight rate itself. However, it is also important to understand the fundamentals and relationships among LPG shipping market variables.

Secondly, as mentioned previously, freight relationships are of vital importance and have been a popular research area. Cointegration test, VAR model, and multivariate GARCH models are the main and only tools adopted in the maritime literature to investigate freight relationships. Such methods are all based on linear and most often binary framework. Moreover, cointegration tests only provide insight into whether there exists a long run relationship between different variables and Granger-causality tests only provide the possible direction of information transmissions. However, we are also interested in exploring the indirect relationships between multiple variables, which means the effect of one variable of another through a mediator. Furthermore, the exact dependence structure among the variables is also of interest. Although multivariate GARCH models explored by recent researchers shed light on this issue, these models often assume linear relationships, which may not be the case in reality. As illustrated by Goulielmos & Psifia (2007), trip and time charter indices exhibit nonlinear dependence structure. Therefore, they concluded that linear and other traditional models may not be appropriate to model the indices' distributions. A model which could account for fat-tail and excess kurtosis behaviors in the multivariate dimension is needed. Furthermore, although several studies have tried to measure the dependency structure between the freight markets, yet no research has modeled the relationships in a dynamic manner. The relationship may not be constant and exhibit time-varying structure. In addition, no research has yet related freight rate formation to the product location arbitrage, which could be a potential important determining factor. There is also no study relating freight rate to spatial patterns of shipping market, i.e. freight rate could be an important determinant of spatial patterns apart from trade imbalances.

Last but not least, with recent technological advancements as well as big data applications in many fields, maritime participants could now make more informed decisions with more data available. One of the examples is AIS data. AIS data is gaining increasing popularity in the maritime industry as it provides accessible and up-to-date information about vessel activities. Shelmerdine (2015) explored the potential use of AIS as a tool to better understand shipping activities by analyzing the information contained in AIS data, which could be used by marine planners and relevant parties. He highlighted the possible analysis with AIS data including vessel tracking, density maps by use of both vessel tracking and point data, as well as quality control of the data. However, AIS data have not often been used in the econometrics field. With the knowledge of a ship's position and destination, coupled with econometric techniques, it should hopefully improve the understanding of shipping market behaviors.

2.6 Conclusion

This chapter conducts the literature review on the tramp shipping freight market, summarizing the major trends and topics. In addition, it reviews the current studies on the methods of freight modeling. As a short summary, for the past few decades, there has been a shift of research attention from building large-scale supply-demand model in a linear regression framework to reduced rate behaviors using time series models, for example, ARIMA or GARCH model to describe freight rate return and volatility behaviors. A further trend from univariate time series analysis to multivariate dimensions has also emerged. Univariate time series models have major limitations in that they model the conditional mean and variance of each series entirely independent of all other series. However, in many cases, the spillover effects, as well as the covariance between series, are of interests. Under such circumstances, VAR and multivariate GARCH models have been used to examine the return and volatility spillover effects between different markets. Regarding the sectors covered, the dry bulk market has received most research attention, followed by crude oil tanker market. In contrast, there has been limited research in the product tanker and LPG freight market. Furthermore, although freight relationships have been a central topic in the literature, methodologies employed are quite uniform, which include cointegration test, VAR models, and multivariate-GARCH models. However, the freight rates may exhibit asymmetric, tail-dependence and time-varying dependence behaviors, which make traditional linear framework not workable.

It is pointed out that in spite of LPG and product tanker shipping's vital importance to the global energy supply chain across the globe, few studies have addressed these sectors, partially due to the diversities of products carried and complexities of trading patterns for the product tanker market, and the niche market nature for LPG shipping market. Moreover, for LPG shipping, existing literature focuses on analyzing the freight rate itself. However, it is also important to understand the fundamentals and relationships among LPG shipping market variables before proceeding to freight analysis alone. Past researchers have studied extensively the spillover effects both in returns and volatilities between freight rates of different markets. However, they could only capture the direction of information transmission and the exact dependence structure has seldom been investigated. As often examined in the financial literature, the price series may exhibit asymmetric, tail-dependence and time-varying dependence behaviors, which make traditional linear framework not workable. However, such dependence information may be particularly useful for portfolio and risk management. Thus, it is also suggested that methodologies, for example, for dependence modeling, well-established in the financial market but not yet used in the shipping market could be explored by researchers with applications in the maritime domain.

On the other hand, no study has analyzed relationships among different variables in an integrated framework. This study proposes an integrated framework using structural equation modeling, which allows all the relationships to be analyzed simultaneously. In this way, both direct and indirect effects can be identified and non-significant effects can be excluded by hypothesis testing. Importantly, mediation effects among variables could be identified, which has seldom been addressed in the shipping literature.

This research complements the existing literature with insights into the LPG and product tanker shipping markets. In particular, this research provides alternative methods for freight relationships modeling, which could have practical significances for both the academy and industry practitioners. No research has yet related freight rate formation to the product location arbitrage, which could be a potential important determining factor. There is also no study relating freight rate to spatial patterns of shipping market, i.e. freight rate could be an important determinant of spatial patterns apart from trade imbalances. For shipowners, knowing the dependency structures between different freight routes would aid their decision in where to deploy the fleet, while understanding the dependency between market variables will aid both chartering and investment decisions. Last but not least, knowing the destination choices of VLGCs based on a set of explanatory variables will help predict future vessel supply patterns in a certain destination region. The next chapter will discuss the research methodologies in details.

CHAPTER 3 RESEARCH METHODOLOGY

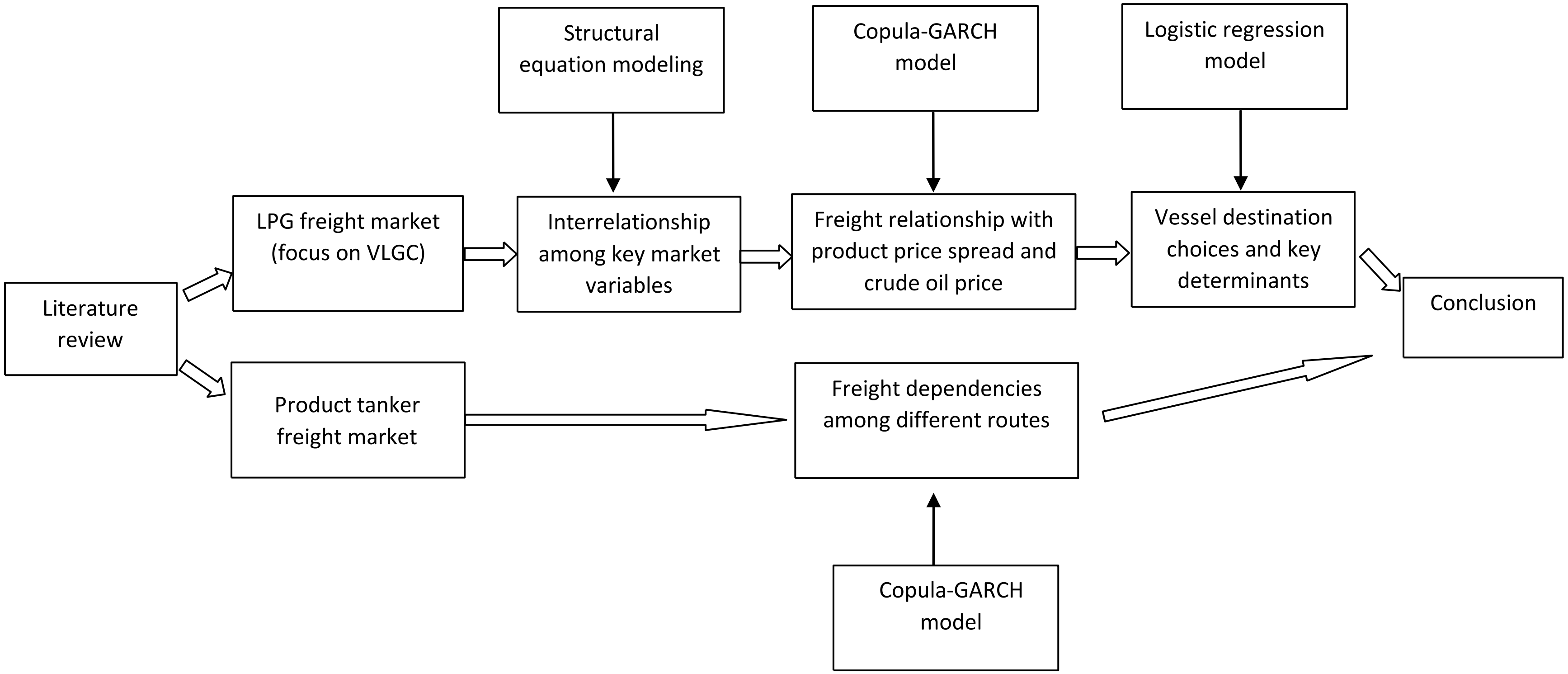
As discussed in Chapter 1, the objective of this research is to provide econometric analyses in the LPG and product tanker market, including relationships among key market variables, freight interdependencies, and destination choice analysis. Based on the literature gaps identified in Chapter 2, this chapter brings forward the proposed methodologies. The purpose of this chapter is to present the framework of how the research has been conducted and the methodology used for each study. The research process flow and detailed methodology are elaborated in this chapter.

3.1 Research process flow

This study starts with the literature review on tramp shipping freight and pinpoints the major trends and topics in freight market research. LPG and product tanker shipping are identified as the market segments for this research due to their importance in energy supply chains and lack of research attention. The VLGC market is selected as the representative of the LPG shipping market because of their significant market share and importance in the gas shipping market. For VLGC market, the study first explores the relationships between the key market variables to have a holistic view of the VLGC market. The variables include market pressure (a ratio of demand over supply), freight rate, new building and secondhand vessel prices. The methodology employed is structural equation modeling. The study then takes a further step by investigating the relationship between freight rate and product price arbitrage and oil prices, apart from the supply and demand factors analyzed in the first step. Both price arbitrage and oil price are considered as crucial for the direction of freight movements. Copula-GARCH is used to identify the dynamic dependency structure. In the last step, the research aims to model vessels' destination choice behaviors and identify their associations with various market factors, from both shippers' and carriers' perspectives. The study uses VLGCs loading from US Gulf as an illustration. Attributes include freight rate, propane price spread, bunker costs and the number of ships in the destination areas. For the product tanker market, as there are many different routes and vessel sizes, it is impossible to analyze in an aggregated manner as in the VLGC market. Thus, a disaggregated approach is taken to explore the dependency structure between various routes using Copula-GARCH model. Based on these analyses, the study provides insights for industry practitioners, such as shipowners for investment and trading decision making.

The overall research process is shown in Figure 3.1.

Figure 3.1 Chart for overall research process flow



3.2 Proposed methods

Based on the methodology used in financial literature and other related fields, some quantitative models and methods could be introduced into the study of LPG and product tanker shipping market. The methods include structural equation modeling, the copula method and logistic regression models for destination choices. The following section briefly reviews each of the method and details will be explained in the next chapters.

3.2.1 Structural Equation Modeling (SEM)

Structural equation modeling is a confirmatory method for data analysis, which assesses the theoretical model of relationships between a set of variables which may include observed variables or unobserved variables. These relationships may be many, directional or non-directional, and can be simple or complex in their arrangements. It can be thought of as a combination of factor analysis models (measurement models) and regression models (structural models). It provides a statistical test for a hypothesized model to evaluate the degree of consistency the proposed model is with the sample data. SEM can assess predictive validity; identify both direct and indirect relationships among variables; as well as specify the level of both explained and unexplained variances in the model. The structural equation model is powerful in the sense that it can easily analyze complex multivariate models, such as mediated models and models with multiple dependent variables, which are difficult to model by traditional multiple regression techniques (Byrne 1998, Schumacker and Lomax 1996). SEM consists of two components, a measurement model assessing unobserved latent variables as linear functions of observed variables, and a structural model showing the direction and strengths of the relationships of latent variables. In this thesis, a structural model is used. It is also referred to as path analysis if only a structural model is used.

The basic equation of the structural model is defined as (Bollen, 1989):

$$\eta = B\eta + \Gamma\xi + \zeta$$

(3.1)

where η is an $m \times 1$ vector of endogenous variables, ξ is a $n \times 1$ vector of the exogenous variables, B is a $m \times m$ matrix of parameters associated with right-hand-side endogenous variables, Γ is a $m \times n$ matrix of parameters associated with exogenous variables and ζ is a $m \times 1$ vector of error terms associated with the endogenous variables.

Structural equation systems are estimated by covariances based structural analysis, in which the difference between the sample covariance and the model implied covariance matrices is minimized (Bollen, 1989). The parameter estimation process starts with some starting values for the parameters. The model-implied covariance matrix ($\widehat{\Sigma}$) is calculated and then compared with the sample covariance matrix (S), resulting in the residual matrix ($S - \widehat{\Sigma}$). If the fit is not good, the values are adjusted and the calculation and comparison are repeated until some criterion is achieved (convergence). This thesis uses the Maximum likelihood (ML) method as the criterion, as it is one of the most common and popular estimation method. There are several frequently used goodness-of-fit measures that can access the result of a SEM model, according to Golob (2003): Chi-square test, which assess the overall fit and discrepancy between the sample and fitted covariance matrices. An insignificant p-value indicates a good model fit; the root mean square error of approximation (RMSEA), which is based on chi-square values and measures the difference between observed and predicted values per degree of freedom. Values closer to 0 represents a good fit; the comparative fit index (CFI), which compares the proposed model with a baseline model with no restrictions. CFI greater than 0.90 indicates a good model. The three goodness-of-fit tests have been together used in the thesis to access model performance.

3.2.2 Copula method for dependence modeling

As mentioned in Section 2.3.4.7, we propose the copula method for freight dependency modeling, which provides a convenient tool for multivariate distribution modeling with only known marginal distributions. This method is particularly of benefits under conditions when multivariate normality does not stand. Covariance and correlations provide simple measures of association between series. However, they are very limited measures in the sense that they are linear and not flexible enough to provide full descriptions of the relationship between time series in reality. Copulas provide an alternative way to link together the individual (marginal) distributions of the series to model their joint distribution. On attractive feature is that they can be applied to link together any type of marginal distributions that are proposed for the individual series. They are particularly useful for modeling the relationships between the tails of the series. Copulas have another useful feature, which is that the dependency parameters could be rendered time-varying, even the marginal follow complicated dynamics. In this thesis, we will use the copula-GARCH model as a particular method.

3.2.3 Logistic regression model

Logistic regression method (Hosmer and Lemeshow, 1989; Allison, 1999) is often applied when the predictor variables are categorical. Compared to multiple regressions, the main difference for logistic regression is that the dependent variables are binary (i.e. 1 or 0). Otherwise, the two methods are very similar in nature. Thus, the logistic regression models the probability of 1 and 0 based on observed values of independent variables. The output of the model could be used for prediction or estimation purpose.

3.2.4 Application of AIS data

One of the main contributions of this thesis is the application of AIS data in the shipping field for freight and spatial analysis. AIS data is gaining increasing popularity in the maritime industry as it provides accessible and up-to-date information about vessel activities. The origination of AIS data comes from the publication of SOLAS convention in 2002, which requires that by 2004, an automatic identification system shall fit all marine vessels greater than 300 gross tonnages (GT) for international voyages, all cargo vessels over 500 GT, and all passenger ships. AIS, being a shipboard transponder, can transmit vessel information automatically containing vessel identity, the current position including longitude and latitude, speed, course, vessel type, among other information.

AIS data has been utilized in various fields to tackle different problems, including tracking and security (Ou and Zhu, 2008; McGillivary et al., 2009); maritime risk analysis and prevention of maritime risks such as collision and oil spill (Eide, 2007; Silveira et al., 2013); marine environment issues such as vessel emissions (Diesch et al., 2013); and spatial planning (Shelmerdine, 2015). Shelmerdine (2015) explored the potential use of AIS as a tool to better understand shipping activities by analyzing the information contained in AIS data, which could be used by marine planners and relevant parties. He highlighted the possible analysis with AIS data including vessel tracking, density maps by use of both vessel tracking and point data, as well as quality control of the data. However, none of them has used AIS as a tool for econometric analysis.

3.3 Copula-GARCH model

Both the freight market and the commodity market vary all the time. The market changes and dependencies could not be fully described by static and linear models. The copula is a useful tool to model the heavy tail, volatility clustering, asymmetric and time-varying correlations of the financial time series (Silvar Filho et al., 2014). A copula function could be decomposed into two parts: uniform marginals and the joint distribution. This study uses the AR-GARCH (1, 1) process with skewed Student-t error term to model the marginal distribution first. Then different families of both constant and time-varying copulas are fitted to study the conditional static and time-varying dependency between the variables.

3.3.1 Copula function

A copula is a function that links together marginal distribution functions to their joint multivariate distribution function (Nelsen, 2006). The application of copulas is through Sklar's theorem (1959), which states that a 2-dimensional joint distribution function F with continuous marginal F_1 and F_2 has a unique copula representation, so that

$$F(x_1, x_2) = C(F_1(x_1), F_2(x_2))$$

(3.2)

Where C is the copula function and $F_1(x_1)$ and $F_2(x_2)$ are the marginal distributions which are uniformly distributed. A copula contains all the dependence information among random variables.

The conditional copula model can be defined by extending Sklar's theorem as:

$$F_{X_1X_2|W}(x_1, x_2|w) = C\big(F_{X_1|W}(x_1|w), F_{X_2|W}(x_2|w)\big|\mathrm{w}\big)$$

(3.3)

Where W being the conditional variable, $F_{X_1|W}(x_1|w)$ and $F_{X_2|W}(x_2|w)$ are the conditional distributions of $X_1|W = w$ and $X_2|W = w$ respectively. The conditional joint distribution of $(X_1X_2)|W = w$ is $F_{X_1X_2|W}(x_1, x_2|w)$.

3.3.2 Dependence measures

There are basically three forms of dependence measures, namely linear correlation, rank correlation and tail dependence. During the past, it is a common practice to use Pearson's correlation to describe the relationship between various price series. However, it could not illustrate the relationship completely as the correlation could only be served as a simple measure of the dependence structure. One important feature of copula is that a copula is invariant under monotonically increasing transformations of its margins. Therefore, a copula of two random variables could completely determine any scale-invariant dependence measures, which under strictly increasing transformations of the variables, remain unchanged (Nelson, 2006). Such dependence measures include Kendall's T (tau), Spearman's ρ, and tail dependence coefficients. Importantly, Pearson's linear correlation coefficient could not be stated in terms of the copula alone; it also depends on marginal distributions. It is known that linear correlation will change when a nonlinear transformation, for example, the logarithm or exponential, of one or both of the variables is applied.

3.3.2.1 Rank correlation

Kendall's T (tau) is a measure of dependence, which is not dependent upon the marginal distributions. It is based on the rank of the variables known as concordance measures. Two random vectors $(X_1, X_2), (Y_1, Y_2)$ are concordant if probability $P\,[(x_1 - y_1)\,(x_2 - y_2) > 0]$ is higher than $P\,[(x_1 - y_1)\,(x_2 - y_2) < 0]$; namely speaking, X_1 and X_2 tend to increase together. They are discordant if the opposite happens. Kendall's T (tau) measures the difference in concordance and discordance probability.

$$\tau = P\,[(X_1 - Y_1)(X_2 - Y_2) > 0] - P\,[(X_1 - Y_1)(X_2 - Y_2) < 0] \tag{3.4}$$

Kendall's T (tau) is within the interval $[-1,1]$. If the variables are independent, the value equals 0.

Another measurement is Spearman's rho, which is the correlation between the transformed variables.

$$\rho_S(X_1, X_2) \equiv \rho_S(F_1(X_1), F_2(X_2)) \tag{3.5}$$

These variables are transformed by their distribution functions to ensure that the transformed variables are uniformly distributed on $[0,1]$.

3.3.2.2 Tail dependence

The third measure focuses on the tail dependence, which is formally defined as the conditional probabilities of quantile exceedances. It measures the dependence when both variables are at extreme values. The upper tail dependence, denoted as λ_u, is

$$\lambda_u(X_1, X_2) \equiv \lim_{q \to I^-} P(X_2 > F_2^{-1}(q) | X_1 > F_1^{-1}(q)), \tag{3.6}$$

where the limit exists $\lambda_u \in [0,1]$. Here F_i^{-1} is the quantile function, namely the inverse of the cdf. The lower tail dependence is defined symmetrically.

3.3.3 Copula classes

There exist various copula families and the copula function could be rendered either static or time-varying. Static or constant copulas presume that the dependence between variables is time invariant. However, the assumption may not be true in reality as a number of empirical research has revealed that the relationships between economic series are time-varying, see Roberedo (2011) for example. Under such circumstances, Patton (2006) extended the standard constant copulas to the conditional/time-varying case. The parameters in the time-varying copulas are allowed to change over time, which allows for more flexible way to describe the relationship between variables. In this study, we consider both constant (time-invariant) and time-varying copulas.

3.3.3.1 Constant copulas

A variety of constant copulas are adopted in this study, including Gaussian, Student-t, Clayton (survival), Gumbel (survival), Frank, Joe, Clayton-Gumbel and Joe-Clayton.

The first copula to introduce is the Gaussian copula and the equation is specified as:

$$C_{Gaussian}(u,v) = \int_{-\infty}^{\Phi^{-1}(u)} \int_{-\infty}^{\Phi^{-1}(v)} (1/2\pi|R|^{1/2}) \exp\{-(u,v)'R^{-1}(u,v)/2\} dudv \qquad (3.7)$$

Where Φ^{-1} is the inverse of the cumulative distribution function (cdf) of the univariate standard normal distribution u and v. $\boldsymbol{R}$ is the correlation matrix implied by the covariance matrix.

The Student-t copula introduces the symmetric tail dependence which Gaussian copula does not capture and is in the following form:

$$C_t(u,v;R,n) = \int_{-\infty}^{t_n^{-1}(u)} \int_{-\infty}^{t_n^{-1}(v)} (\Gamma((n+2)/2)|R|^{-1/2})/(\Gamma(n/2)(n\pi)) \cdot (1 + 1/n\,(u,v)'R^{-1}\,(u,v))^{-(n+2)/2} dudv \qquad (3.8)$$

Where R is the correlation matrix and n is the degree of freedom parameter, while t_n is the univariate Student-t cdf with degree-of-freedom parameter n and the univariate inverse cdf of the t-distribution is denoted by ${\mathrm{t}_n}^{-1}$.

The three Archimedean copulas employed in this study are Clayton, Gumbel and Frank copulas.

The Clayton copula function introduced by Clayton (1978) is an asymmetric copula with higher probability concentrated in the lower tail and can be written as

$$C_{Clayton}(u,v) = \left(u^{-\theta} + v^{-\theta} - 1\right)^{-1/\theta},\ \theta \geq 0 \tag{3.9}$$

Where θ being the copula parameter.

Gumbel Copula (Gumbel, 1960) on the other hand, has upper tail dependence and could be specified as

$$C_{Gumbel}(u,v) = \exp\left\{-[(-\ln u)^{\theta} + (-\ln v)^{\theta}]^{1/\theta}\right\},\ \theta \geq 1. \tag{3.10}$$

Frank copula (Genest, 1987) is a symmetric copula given by

$$C_{Frank}(u,v) = -1/\theta \ln[1 + (\exp(-\theta u)\,(\exp(-\theta v) - 1))/(\exp(-\theta) - 1)], \theta \in \mathbb{R}\backslash\{0\}. \tag{3.11}$$

The Joe copula (Joe, 1993) is defined as

$$C_{Joe}(u,v) = 1 - [(1-u)^{\theta} + (1-v)^{\theta} - (1-u)^{\theta}(1-v)^{\theta}]^{1/\theta}, \theta \geq 1. \tag{3.12}$$

The Clayton-Gumbel and Joe-Clayton copulas (Joe and Hu, 1996), also known as BB1 and BB7, can model flexibly different lower and upper tail dependence structures. For BB1, the model is given by

$$C_{BB1}(u,v) = (1 + [(u^{-\theta} - 1)^{\delta} + (v^{-\theta} - 1)^{\delta}]^{1/\delta})^{-1/\theta} \tag{3.13}$$

Where $\theta > 0$ and $\delta \geq 1$; $\tau^L = 2^{-1/(\delta\theta)}$, $\tau^U = 2 - 2^{1/\delta}$.

A BB7 copula can be defined as

$$C_{BB7}(u, v) = 1 - (1 - [1 - (1 - u^\theta)^{-\delta} + (1 - [1 - (1 - v^\theta)^{-\delta} - 1]^{-1/\delta})^{1/\theta}$$

(3.14)

Where $\theta \geq 1$ and $\delta > 0$; $\tau^L = 2^{-1/\delta}$, $\tau^U = 2 - 2^{1/\theta}$.

Rotated copulas are also considered in this study. Many copulas, for example, Gumbel and Clayton copulas cannot model negative tail dependencies, which many series may exhibit. These copulas can be rotated based on the original un-rotated copula to derive a new copula. This study considers $180°$ rotated Clayton, Gumbel, and BB1 copulas, which are also known as survival copulas. Cech (2006) defined the survival copulas as

$$C_{180}(u, v) = u + v - 1 + C(1 - u, 1 - v).$$

(3.15)

3.3.3.2 Time-varying Copulas

Patton (2006) applied Sklar Theorem (1959) to introduce the time-varying conditional copulas. In a time-varying copula, the parameters are allowed to evolve over time. This study considers four types of time-varying copulas, including time-varying Gaussian, Student-t, Rotated Gumbel and Symmetrised Joe-Clayton (SJC) copulas proposed by Patton (2006) and Patton (2013). Time-varying parameters for Gaussian and SJC copulas are defined following Patton (2006)'s method, while parameters for time-varying Student-t and Rotated Gumbel copulas evolve based on Generalized Autoregressive Score (GAS) models proposed by Creal et al. (2013) and Patton (2013).

The parameter ρ of time-varying Gaussian copulas are defined as (Patton, 2006)

$$\rho_t = \widetilde{\Lambda}\left(\omega_\rho + \beta_\rho \rho_{t-1} + \alpha_\rho \cdot 1/10 \sum_{i=1}^{10} \Phi^{-1}(u_{t-i}) \Phi^{-1}(v_{t-i})\right)$$

(3.16)

where Φ^{-1} is the inverse of the standard normal cumulative density functions and $\widetilde{\Lambda}(x) \equiv (1-e^{-x})/(1+e^{-x})$ is the modified logistic transformation in order to keep the parameter ρ_t in (-1, 1) at all times.

For time-varying SJC copula, the constant version is symmetrised Joe-Clayton copula, which was proposed by Patton (2006), is a slight modification from BB7 copula.

$$C_{SJC}(u,v) = 0.5 \cdot (C_{BB7}(u,v) + C_{BB7}(1-u,1-v) + u + v - 1)$$

(3.17)

The parameters evolve based on the following equations:

$$\tau_t^U = \Lambda(\omega_U + \beta_U \tau_{t-1}^U + \alpha_U \cdot 1/10 \sum_{i=1}^{10} |u_{t-i} - v_{t-i}|)$$

(3.18)

$$\tau_t^L = \Lambda(\omega_L + \beta_L \tau_{t-1}^L + \alpha_L \cdot 1/10 \sum_{i=1}^{10} |u_{t-i} - v_{t-i}|)$$

(3.19)

where $\Lambda(\mathrm{x}) \equiv (1+e^{-x})^{-1}$ is the logistic transformation to ensure the parameters τ^U and τ^L stay in (0,1) all the time.

For time-varying Student-t and Rotated Gumbel copula, the GAS model proposed by Creal et al. (2013) is used to depict the evolution process of the time-varying copula parameter (δ_t). One advantage of GAS model is that it can fully use the likelihood information. The driver of time variation is a score function. The original parameter δ_t is transformed to f_t to ensure that the correlation parameter can always stay in (-1,1). Following Patton (2013), f_t is defined as

$$f_t = \hbar(\delta_t) \Leftrightarrow \delta_t = \hbar^{-1}(f_t)$$

(3.20)

$$\text{where } f_{t+1} = \omega + \beta f_t + \alpha I_t^{-1/2} s_t$$

(3.21)

$$s_t \equiv \partial / \partial \delta_t \log C(u_t, v_t; \delta_t)$$

(3.22)

$$I_t \equiv E_{t-1}[s_t s_t'] = I(\delta_t)$$
(3.23)

where $\delta_t = 1 + \exp(f_t)$ for Gumbel copula to ensure the parameter $\delta_t > 1$ at all time. For Student-t copula, $\delta_t = (1 - \exp\{-f_t\})/(1 + \exp\{-f_t\})$ to keep the parameter in the interval (-1,1). Only the correlation parameter is time-varying for Student-t copula, while the degree of freedom parameter is assumed to be constant over time.

3.3.4 Statistical inferences

A two-step estimation method is employed to compute the copula parameters, namely Inference Functions for Margins (IFM), which is firstly proposed by Shih and Louis (1995). IFM method could be considered as the Maximum Likelihood Estimation (MLE) of the dependence structure given the estimated margins.

Let z_1 , z_2 be two random variables, where z_i has parametric cumulative distribution function (cdf) $F_i\ (z_i;\ \alpha_i)$ and corresponding density functions by $f_i\ (z_i;\ \alpha_i)$. α_1, α_2 and θ_c are the parameters to be estimated for the marginals and the copula respectively. In IFM estimation, firstly, the parameters α_i of the marginal are estimated by

$$\hat{\alpha}_i = \arg\max \textstyle\sum_{t=1}^{T} \ln f_i(z_{ti}; \alpha_i) \qquad i = 1,2.$$
(3.24)

And then the associated parameters $\hat{\theta}_c$ given $\hat{\alpha}_i$ are estimated by

$$\hat{\theta}_c = \arg\max \textstyle\sum_{t=1}^{T} \ln c(F_1\ (z_{t1}; \hat{\alpha}_1), F_2\big((z_{t2}; \hat{\alpha}_2); \theta_c\big)$$
(3.25)

In this situation, the number of parameters estimated during each maximization task is small, thus the computational difficulty could be reduced to a large extent. Patton (2006) shows that this IFM method generates asymptotically normal and efficient parameter estimates. IFM method has another notable benefit, that is, the marginal specifications are able to be tested by standard diagnostic techniques to make sure of a good fit for the data. In the context of Copula-GARCH model, during the post-estimation examination, Ljung-Box test for autocorrelation and

ARCH test for the existence of any remaining ARCH effects of the standardized residuals are performed.

3.3.5 Marginal specification

Based on the IFM method, the marginals are firstly specified parametrically by the GARCH framework, which could capture most of the stylized features observed in freight series, such as volatility clustering and fat tails. In this study, we adopt Bollerslev (1986) standard GARCH model. The conditional variance is allowed to depend on previous own lags in the GARCH model. In most cases, GARCH (1,1) should be sufficient and complex specification search hardly increases the model's forecast ability ((Hansen and Lunde, 2001). Let y_t be a time series of freight returns whose mean equation is given by

$$y_t = E(y_t|\Omega_{t-1}) + \varepsilon_t,$$

$$\varepsilon_t = \sigma_t z_t,$$

(3.26)

where Ω_{t-1} is the available information at time $t-1$ and ε_t are the random innovations with $E(\varepsilon_t) = 0$. z_t is i.i.d. random variable with mean 0 and variance 1.

For a given time series y_t, the GARCH (1,1) model could be written as

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

(3.27)

Where σ_t^2 is the conditional variance, which is dependent on both a long-term average value (dependent on ω), information about past volatility ($\alpha\varepsilon_{t-1}^2$) and past conditional variance ($\beta\sigma_{t-1}^2$). When $\omega > 0$, $\alpha > 0$, $\beta > 0$ and $\alpha + \beta < 1$, the conditional variance process is stationary and positive. The sum ($\alpha + \beta$) measures the persistence of variance. The persistence of shocks to volatility becomes greater when this sum approaches unity. If $\alpha + \beta > 1$, the GARCH process is not stationary and the shocks tend to increase instead of declining.

For the conditional mean, we model it as an ARMA (p, q) process, which consists of an AR part of order p and an MA part of order q:

$$y_t = \mu + \theta_1 y_{t-i} + \cdots + \theta_p y_{t-p} + \emptyset_1 \varepsilon_{t-1} + \cdots + \emptyset_q \varepsilon_{t-q} \tag{3.28}$$

θ being the autoregressive coefficients and $\emptyset$ being the moving average coefficient. ε_t is the innovations. ε_t is assumed to be skewed-t distributed to account for the fat tail and skewness behavior of freight rate returns. In many cases, AR (p) process is used due to its simplicity.

CHAPTER 4 ECONOMETRIC ANALYSES OF LPG SHIPPING MARKET

This chapter provides econometric analyses of the LPG shipping market based on the models described in Chapter 3. Specifically, this chapter is divided into two parts. In Section 4.1, first, a structural equation model is developed to analyze the different relationships between supply/demand, freight rate, newbuilding and secondhand vessel prices within the VLGC market. Six hypotheses are initially proposed and all are supported. In Section 4.2, the dependence dynamics among LPG freight rates, crude oil price, and propane location arbitrage have been studied. Copula-GARCH model is applied to estimate dependencies. Different types of copulas with both time-invariant and time-varying dependence structures are fitted and their suitability has been compared. Section 4.3 investigates vessels' destination choice behaviors and identify their associations with various market factors, from both shippers' and carriers' perspectives. The study uses VLGCs loading from US Gulf as an illustration. Attributes include freight rate, propane price spread, bunker costs, and the number of ships in the destination areas. It also identifies the effects of the Panama Canal expansion on destination choices, by dividing sample data into two sub-periods: before and post expansion. Furthermore, both aggregate and disaggregate analysis for different ports are provided.

The first part is to address the interrelationship within the LPG shipping market, while the second part is to investigate additional influencing factors apart from supply and demand balance. Shipping freight rates are highly volatile and can be influenced by various factors. One of them is product location arbitrage, which has been valued by industry practitioners, however, seldom studied in the academic field. The oil price effects on the arbitrage and freight rates are also of interests. The last part identifies vessels' spatial patterns and its association with market variables.

4.1 An integrated analysis of interrelationships within the very large gas carrier (VLGC) shipping market: a structural equation modeling approach

The global shipping market has long been defined as having four closely related sub-markets (Stopford, 2009): freight market, secondhand market, new building market, and demolition market. In the freight market, freight rates are negotiated between shipowners and charterers. The newbuilding and demolition markets both directly affect the supply side of international shipping. New vessel prices reflect market expectations due to the time lag from the ordering to the delivery of the vessel (Beenstock, 1985). In the secondhand market, ships change hands between different owners. Demand for shipping services stems from global seaborne trade. A higher demand will push up freight rates, which in turn motivates owners to buy more ships so as to take advantage of improved earnings. Shipowners may first consider buying a secondhand ship, as these vessels are immediately available. Higher buying activity, however, will raise secondhand vessel prices and owners will turn to shipyards to order new ships. This, in turn, will drive up newbuilding prices. When the new ships are delivered, the supply of tonnage increases and, *ceteris paribus*, freight rates decrease. During a low freight rate environment, sale and purchase activity is discouraged. Less trading and ordering activity could then put downward pressure on secondhand and newbuilding prices. The various relationships have been separately investigated extensively in the bulk shipping market (Tinbergen, 1934; Koopmans, 1939; Hawdon, 1978; Norman's ,1979; Wergeland, 1981; Strandenes, 1984; Beenstock, 1985; Beenstock and Vergottis, 1989a, 1989b, 1993; Tsolakis et al., 2003; Adland et al., 2006; Alizadeh and Nomikos, 2007; Xu et al., 2011; Kou et al., 2014; Adland and Jia, 2015; Kou and Luo, 2015). However, no study has yet used an integrated framework to examine both the direct and indirect effects among the variables. Failing to do so could result in neglecting important mediating effects among the variables.

The objective of this study is to analyze the various relationships between demand/supply and freight rates, and secondhand and newbuilding prices in the

VLGC market. Six hypotheses are brought forward and tested using Structural Equation Modeling (SEM). Important implications are drawn for LPG shipowners and related agents, such as charterers and asset players (i.e. private equities). This study could help shipowners combine anticipated changes in freights rate and vessel prices with information concerning demand and supply changes, thus enabling them to make more informed decisions regarding vessel financing, ordering, and purchasing of vessels.

4.1.1 Hypotheses

Based on the literature review in Chapter 2 and the understanding of the shipping market, Six hypothesized relationships are initially proposed. These hypotheses will subsequently be supported or rejected based on the significance test of the paths. Table 4.1 lists the variables to be included and their abbreviations.

Table 4.1 Variable names and Abbreviations

Variable Name	Abbreviation
Market pressure	MP
Secondhand vessel price	SH
Newbuilding price	NB
Freight rate	FR

Freight rates and vessel prices (both new and old) are outcomes of the supply-demand dynamics in their respective markets, namely the freight, newbuilding and secondhand ones. However, one common factor should link the three markets together, this being the international seaborne trade (Kou and Luo, 2015). An increase in the demand for shipping could lead to rising freight rates, which may prompt more demand for ships, thereby increasing both ship prices and the number of ships ordered. An eventual delivery of ships will put downward pressure on freight rates and this can also reduce ship prices as there is lackluster demand for more ships. On the other hand, freight rates and vessel prices are set by demand relative to supply, so high supply in itself, or even increasing supply in isolation, need not affect rates negatively. It all depends on what happens to demand during the same time period. To measure the market dynamics/pressure, a ratio between demand and supply is used, defined as ton-mile demand/ton-mile supply. Both demand and supply are measured in the same unit. Therefore, we have the following hypotheses 1 to 4, with supply/demand linking the markets.

Freight rate is a function of supply and demand dynamics, namely how demand changes relative to supply. When the demand for seaborne transportation increases, freight rates tend to rise accordingly. For instance, a surge in demand for raw materials from emerging economies with scarce resources pushed up the dry bulk freight rate to a high level in the early 2000s (Nomikos et al. 2013). On the other hand, a significant delivery of new ships to an existing fleet would exert a negative effect on freight rates if demand remains unchanged. A low level of shipping investments could reduce supply and have a positive impact on freight rates. An example is the surge in dry bulk freight rates during the 2000s, due to the prolonged period of underinvestment in new capacity during the 1980s and 1990s (Nomikos et al. 2013). Hence, the first hypothesis tests the relationship between market pressure (demand/supply) and freight rates. A higher market pressure indicates a relatively tight market with higher demand relative to supply.

Hence, hypothesis 1 is set as:

H1: Freight rates are positively related to market pressure (demand/supply ratio) for freight services

Higher demand for shipping services would attract plenty of buyers in the sale and purchase market, interested to, profitably, cover the increasing cargo transportation requirements. This could lead to higher prices. On the other hand, for example, as pointed out in the Platou Report (2015), the weak dry bulk tonnage demand in 2014 led to a decrease in secondhand values between 15 and 25 percent (depending on ship age), for the Handy, Supramax and Panamax categories. Sale and purchase activities are reduced in an overcapacity environment, as downward market expectations may prevail when there is excess capacity and freight rates might fall as a result. As an example, Lloyd's List (2010) reports that a flood of newbuilding handymax vessels could push secondhand vessel prices down 20% in the next two years, compared with 2010 level. Thus, hypothesis 2 is shown below:

H2: Secondhand vessel price is positively related to market pressure (demand/supply ratio)

In anticipation of growing seaborne demand, shipowners may decide to place more orders at shipyards. Competition for shipbuilding berths will drive up newbuilding prices. The Platou Report (2015) records higher newbuilding prices in 2013, compared with the previous year, on the back of increased demand and long delivery times, as orderbooks become thicker. Same as for the sale and purchase market, when there are too many ships sailing, owners tend to reduce ordering activities at shipyards, given negative market expectations. When shipyards have too few orders, they may have to drop their prices to tempt in buyers (Stopford, 2009). Hawdon (1978) has found a statistically significant negative coefficient for the fleet size on newbuilding prices, which indicates the depressing influence of overcapacity on ship prices. Thus, hypothesis 3 is proposed as:

H3: Newbuilding price is positively related to market pressure (demand/supply ratio)

Prices, particularly those of secondhand ships, correlate strongly with freight rates (Haralambides et al., 2005). Freight rates are regarded as the primary influencer of ship prices (Stopford, 2009). Lows and highs in the freight market are transmitted into the secondhand market. When freight rates are high, owners will initially search for a ship in the sale and purchase market, as these ships are immediately ready for trading. The thick volume of trading will put upward pressure on secondhand vessel prices. As such, we have Hypothesis 4:

H4: Secondhand vessel price is positively related to freight rate

Shipowners choose investment strategies in order to maximize the discounted cash flow of profits, given their expectations on how freight rates will develop (Gkochari, 2015). With positive expectations for the shipping market, shipowners are inclined to order more ships. During booms, when a shipyard has received many orders and owners compete for the few building berths available, prices increase dramatically. The opposite happens in a recession. Therefore, Hypothesis 5 is derived.

H5: Newbuilding price is positively related to freight rate

When secondhand prices are too high, owners would place more new orders at shipyards. Active ordering will increase newbuilding prices. Furthermore, during booms and troughs, secondhand prices are more volatile and respond to market information more quickly than newbuilding prices (due mostly to delivery times). Therefore, newbuilding prices have little impact on secondhand prices (Chen et al. 2014). Hypothesis 6 is proposed as such:

H6: Newbuilding price is positively related to secondhand vessel price

Table 4.2 summaries the hypotheses and their supporting literature. All hypotheses are developed either by previous literature or market reports. For H2, the effects of market pressure on secondhand prices, has not been investigated in the academic field, although it has been reported in various market reports. Changes in secondhand prices appear to be more determined by changes in freight rates (Strandenes, 1984; Tsolakis et al., 2003; Alizadeh and Nomikos, 2007; Lun et al., 2013). Furthermore, newbuilding prices may not be suitably explained by a supply-demand framework (Beenstock and Vergottis, 1989a; 1989b) as mentioned above. However, these two hypotheses are included due to their possible relationships, i.e. that vessel prices might be influenced by supply/demand dynamics apart from freight rates, as it appears in market reports. Other hypotheses, although supported in bulk shipping literature, have not been tested in the VLGC market. The shipping market is quite fragmented and different markets may have different characteristics. Unlike other shipping markets such as dry bulk market with diversified trading routes, LPG transport has limited main trading patterns, which leads to more price volatility with higher sensitivity to market condition changes (Adland et al., 2008). Furthermore, VLGCs are owned by a handful number of owners due to a higher capital intensity which creates higher barriers to entry and the niche feature of the LPG shipping market, compared to more diversified shipowner portfolio found in other shipping markets. These characteristics contribute to the uniqueness of the LPG freight market. Therefore, the significance of these different relationships as mentioned in the above 6 hypotheses in the VLGC market needs to be tested.

Table 4.2 Hypotheses and their supporting literature

Hypotheses	Supporting Literature
H1: Freight rates are positively related to market pressure (demand/supply ratio) for freight services	Tinbergen (1934); Hawdon (1978); Wergeland (1981); Beenstock and Vergottis (1989a, 1989b, 1993a)
H2: Secondhand vessel price is positively related to market pressure (demand/supply ratio)	The Platou Report (2015); Lloyd's List (2010)
H3: Newbuilding price is positively related to market pressure (demand/supply ratio)	Hawdon (1978); The Platou Report (2015);
H4: Secondhand vessel price is positively related to freight rate	Strandenes (1984); Tsolakis et al. (2003); Alizadeh and Nomikos (2007); Lun et al. (2013)
H5: Newbuilding price is positively related to freight rate	Xu et al. (2011); Lun et al. (2013)
H6: Newbuilding price is positively related to secondhand vessel price	Tsolakis et al. (2003); Kou et al. (2014)

4.1.2 Data

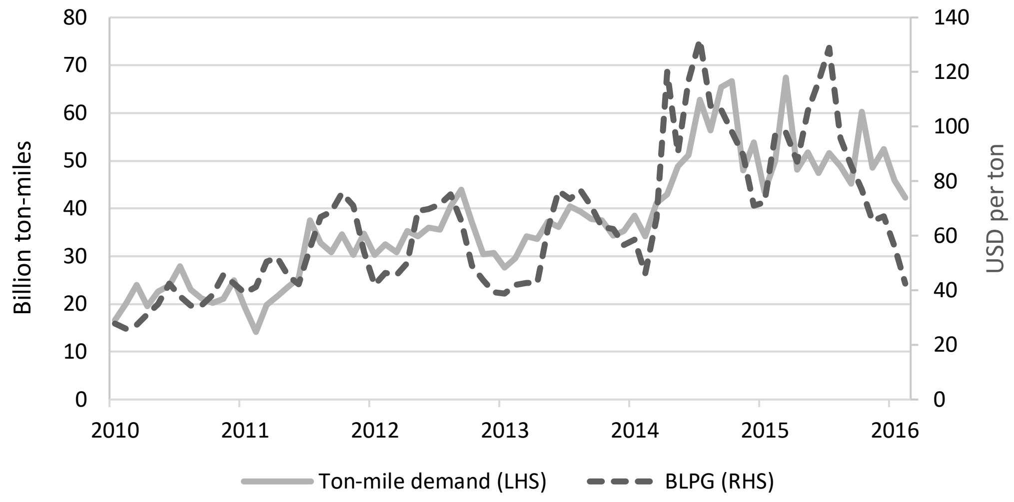
In this analysis, the data sets consist of monthly VLGC freight rates, monthly ton-mile demand, monthly ton-mile supply, monthly secondhand and newbuilding vessel prices from Jan 2010 to Mar 2016. Freight rate is the monthly average of BLPG index published by Baltic Exchange, which is the benchmark index for LPG freight rates and tracks the dollar per ton rate for VLGCs loading 44,000mt of LPG from Ras Tanura and discharging in Chiba. Ton-mile demand is calculated by taking the sum of each vessel's loading volume, multiplied by the distance she travels from the loading port to the discharging port in one month, based on Waterborne LPG report (IHS, 2016), which tracks all VLGC liftings (including the ship's name, quantity, types of cargo, voyage origin and destination). Ton-mile supply is defined as:

$$Fleet\ size * unit\ carrying\ capacity\ (44{,}000mt) * average\ sailing\ speed \\ * 24\ (24\ hours\ a\ day) * 25\ (assume\ 25\ sailing\ days)$$

The average sailing speed is derived based on AIS data, which constantly tracks all VLGCs' speed. Then, market pressure can be calculated by taking the ratio of demand over supply. Vessel prices are extracted from Steensland research (2016) and all prices are quoted in million dollars. Fleet data is obtained from Sea-web (2016).

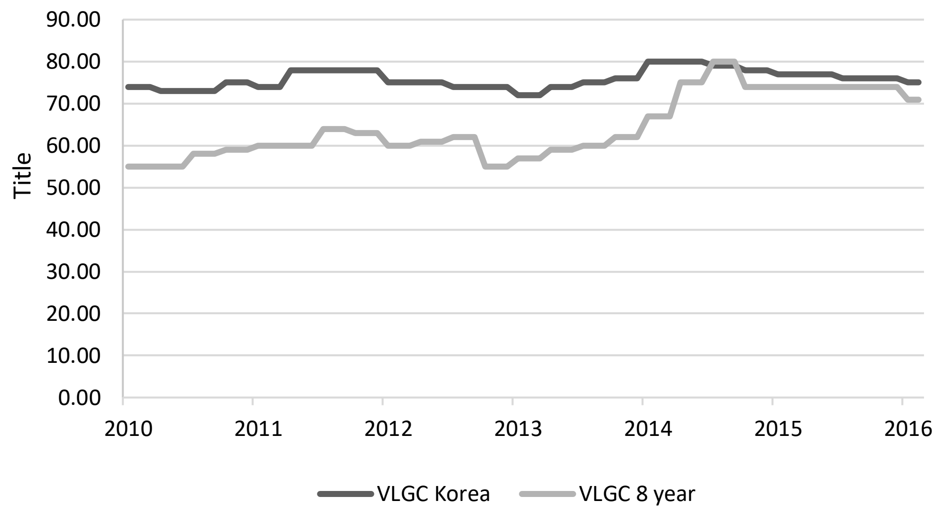
Figure 4.1 indicates the historical BLPG and ton-mile demand. At a first glance, the VLGC freight rate is very volatile, especially after 2013. As noted in Adland et al. (2008), main trading routes for LPG transport are limited (from Arabian Gulf to Asia and recently from the US to Asia and Europe), something that creates more price volatility, as the sensitivity to market conditions tends to increase, compared to other shipping markets with diversified trading patterns and cargo bases. The second observation is that ton-mile demand is also quite volatile, and it changes rapidly from month to month. The reason is that much LPG trade occurs due to location price arbitrage. A location arbitrage is a trading strategy to profit from product price differences in different locations considering the cost of transportation. An example would be in Apr 2015, Asian LPG buyers taking US cargoes could make a profit of $35/t, taking into account the cost of transportation. The arbitrage window was opened due to softening freight rate caused by vessel availability and weaker spot cargo prices at LPG export terminals near Houston (Argus, 2015). Consequently, transportation volumes could change a lot when price arbitrage becomes wider or narrower. Therefore, the *constant short-term demand* assumption of many bulk shipping markets does not apply in the VLGC market. Furthermore, the US shale gas revolution in the US has shifted this country from a net LPG importer to a net exporter. This drove up the ton-mile demand substantially during 2013 and 2014. Last but not least, there is a clear positive relationship between ton-mile demand and freight rates. Freight rates shot up in the first half of 2014 and 2015 on the back of improved ton-mile demand. On the other hand, the rapid drop in freight rates since the second half of 2015 is mainly due to a massive expansion of fleet size. In Jan 2014, the VLGC fleet consisted of 159 vessels, while in Jan 2016, this number increased to 208; a massive increase of 30% in just two years (Sea-web, 2016). Figure 4.2 shows the new and 8-year-old VLGC price developments. The two prices generally move in parallel, with the newbuilding price being stickier than secondhand price. When the freight market is attractive, secondhand vessels might cost more than newbuildings due to high market expectations, and buyers are willing to pay a premium so their vessels could be traded immediately, as happened during the freight boom in the second half 2014.

Figure 4.1 Historical BLPG index and Ton-mile demand



Source: drawn by author, based on Baltic Exchange and IHS.

Figure 4.2 VLGC newbuilding and 8-year-old vessel price



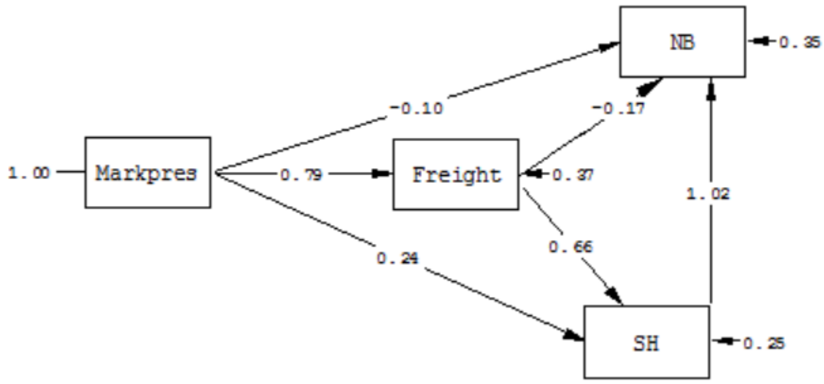
Source: drawn by author based on Steensland Research.

4.1.3 Results and Discussions

4.1.3.1 Results

The theoretical framework depicted in Figure 4.3 has 6 hypothesized relationships among the 4 Variables, market pressure (MP) as the exogenous variable; freight rate (FR); newbuilding price (NB); and secondhand price (SH) as endogenous variables. Figure 4.3 illustrates the path diagram from the structural modeling analysis utilizing LISREL software.

Figure 4.3 Path diagram of the hypothesized model



Source: Author.

The figures shown on the arrows are standardized coefficients. Unstandardized coefficients are the effects measured in absolute magnitude, i.e. the resulting change in dependent variable from a unit change in the independent variable. Standardized coefficients are standardized solutions, where all variables are standardized first. Only standardized parameter estimates can be meaningfully compared with each other. Therefore, the standardized coefficients are shown. There is no statistical difference between unstandardized and standardized coefficients. Using the goodness-of-fit tests mentioned in Section 3.2.1, the results show a chi-square statistic of 0.000, which means a perfect fit of the model. RMSEA (0.000) and CFI (1) all indicate a good fit of the proposed model. However, not all paths are significant according to t-statistics. As shown in Table 4.3, the t-test of the paths from MP to NB, and FR to NB are not significant, which implies that Hypothesis 3 and 5 may not be justified.

Table 4.3 Results of the hypothesized structural equation model

Hypothesis	Relationship	Standardized coefficient
H1	MP →FR	0.79**
H2	MP →SH	0.24**
H3	MP →NB	**-0.1**
H4	FR →SH	0.66**
H5	FR →NB	**-0.17**
H6	SH →NB	1.02**

**significant at 1% and *significant at 5%.

Source: Author.

To validate these two hypotheses and assess whether the proposed model in Figure 4.3 has the best fit and parsimony, alternate nested models are compared by deleting first the path MP to NB, as Model 2, and then dropping both the path MP to NB and FR to NB, as Model 3. Table 4.4 reports various model fit index for the two nested models. All models have good RMSEA and CFI index. It is often recommended to compare the fit of current model to alternative models. An often-asked research question is a model better with an additional path compared to an otherwise identical model without this path? The chi-square difference tests (SCDTs) are performed to test whether a given model fits significantly better or worse than a competing model. In this study, the question is if the proposed model (M1) in Figure 4.3 shall be accepted compared to the other two alternative models. SCDTs are referred to as "likelihood ratio tests'. The test computes the difference between Chi-sq values for the proposed model (M1) and the alternate model M2, with degrees of freedom (df) equal to the difference of df between these two models. Tests between M2 and M3 are then performed. Table 4.4 summarizes the results. A significant chi-square difference test value should imply that the free parameters in the baseline model (which were constrained in the nested model) contribute to significant improvement in model fit, thus the hypothesized model will be accepted. On the other hand, the alternate model shall be accepted as a more parsimonious model, without sacrificing significant loss in model fit, when there is no difference in explanation of construct covariances.

An insignificant chi-square difference test value indicates that the two models fit equally well statistically, so the parameters in question can be eliminated from the model. As shown in Table 4.4, the proposed model (M1) is rejected to the alternative models (M2 and M3) at a significant level of 5%. Therefore, M3 is selected as the final model with good fit and parsimony. Figure 4.4 indicates the final path diagram.

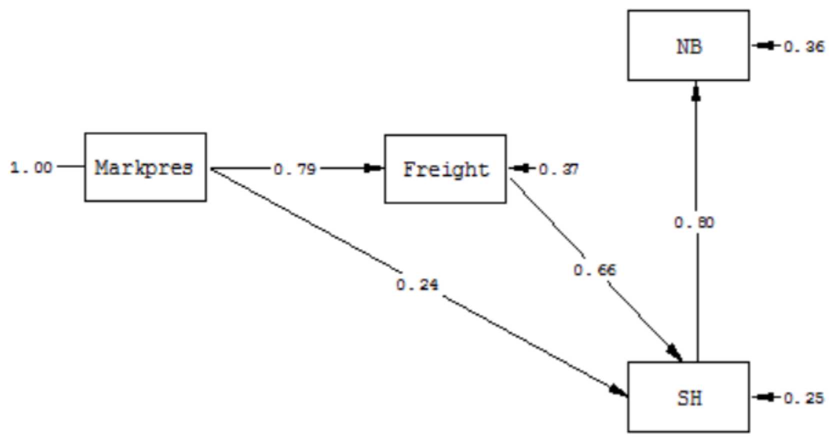
Table 4.4 Comparison between alternate nested models

Model	df	Chi-sq	Chi-square difference	df difference	SCDT ($\alpha = 0.05$)	RMSEA	CFI
M1: Hypothesized Model	1	0.000				0.000	1
M2: Remove the link MP →NB	2	0.69	0.69	1	Not significant	0.000	1
M3: **Remove the link MP →NB, FR→NB**	3	3.4	2.71	1	Not significant	0.043	1

*significant at 5% level, **significant at 1% level. Chi-sq difference tests are performed between M1 and M2, M2 and M3.

Source: Author.

Figure 4.4 Results for final structural equation model (M3)



RMSEA=0.043 CFI=1.00

Source: Author.

The total and indirect effects of the different relationships among variables are reported in Table 4.5. Direct effects refer to the relationship directly connecting two constructs, while indirect effects indicate the relationship portraying a series of relationships with the involvement of a mediator variable. Results suggest all six hypotheses are supported. Although, H3 (MP→NB) and H5 (FR →NB) are not justified due to insignificant t-statistics of the coefficients, their total effects are significant considering indirect effects (total effects of H3: 8.27, H5: 0.04).

Table 4.5 Total and indirect effects

Hypothesis	Relationship	Standardized coefficient	Total effects	Indirect effects	Standardized total effects	Standardized indirect effects	Hypothesis
H1	MP →FR	0.79**	161.90** (14.38)		0.79		Supported
H2	MP →SH	0.34**	33.02** (3.24)	22.76** (5.86)	0.76	0.53	Supported
H3	MP →NB		8.27** (1.09)	8.27** (1.09)	0.61	0.61	Supported
H4	FR →SH	0.66**	0.14** (0.02)		0.66		Supported
H5	FR →NB		0.04** (0.01)	0.04** (0.01)	0.53	0.53	Supported
H6	SH →NB	0.80**	**0.25** (0.02)**		0.80		Supported

** Significant at 1% level, * significant at 5% level. t values are in parentheses.

Source: Author.

The following section will provide a detailed discussion on the different relationships.

4.1.3.2 Discussions

Freight rate

Freight rate is positively affected by the market pressure, which is measured by ton-mile demand relative to supply. The results indicate that both ton-mile demand and supply play an important role in freight rate formation process. This has significant implications for market players when the orderbook of VLGC is very high. If ton-mile demand continues to grow at a healthy rate, this will drive up freight rates, in spite of the new vessels that are coming into the market. However, if ton-mile demand stagnates, the new vessels to be delivered will further push down the freight rate.

Secondhand and newbuilding vessel price

The results show that the prices of both newbuilding and secondhand vessels are influenced by freight rates. The findings also suggest that the secondhand price is directly affected by freight rate, while the relationship between freight rate and newbuilding price is rather indirect, through the secondhand price acting as a mediator. As shown in Table 4.3, the coefficient of H5: FR→NB is negative, which is in contrary to our common understanding. However, considering the total effects, which include the indirect effect via secondhand price, the effect is positive. The result is in line with the market mechanism: When freight rates are high, shipowners tend to acquire a secondhand vessel, which is immediately ready for trading in the sale and purchase market, to take advantage of the rising freight market. This will push up secondhand prices. When secondhand vessels are not available or prices are too high, owners will obtain additional shipping capacity by ordering new ships, which then drives up newbuilding prices. Secondhand price will serve as the guideline for newbuilding price movement. The finding also resonates Kou and Luo (2015)'s conclusion that secondhand prices are more sensitive to freight rate changes than newbuilding prices, as evidenced in the standardized total effects from FR→SH being higher than that from FR→NB. Adland and Jia (2015) also concluded that newbuilding prices are 'stickier' compared to secondhand prices. It is also pointed out by them that newbuilding and secondhand prices may not be directly comparable due to time-varying delivery lag. However, the delivery lag cannot be computed without actual detailed newbuilding contract and delivery data. Furthermore, since the delivery lag is time-varying and differs across shipowners (Adland and Jia, 2006), an estimated constant delivery lag may not be an accurate measure of the time difference. Considering these factors, it would be more feasible and meaningful to study the contemporaneous relationship.

The effects of supply and demand dynamics on secondhand prices are mostly indirect, through freight rate as a mediator. Table 4.5 shows that the standardized total effect from MP → SH is 0.76, among which the indirect effect through FR is 0.53. Furthermore, market pressure affects newbuilding vessel prices mainly through the secondhand market as shown in Table 4.5. The direct effect from MP → NB is not siginificant, however, the indirect effect through SH is significant.

This finding is in line with previous literature, according to which the newbuilding price cannot be appropriately explained by supply and demand mechanisms (Beenstock and Vergottis, 1989a; 1989b) and that freight rates play a dominant role in secondhand prices (Strandenes, 1984; Tsolakis et al., 2003; Alizadeh and Nomikos, 2007; Lun et al., 2013). This can be further explained since secondhand vessels are more market-driven and more influenced by the freight market, whereas the shipbuilding industry is supply and cost driven. Countries would not adjust their shipbuilding capacity, something that involves a lot of investment, to speculative movement of prices.

4.1.3.3 Implications

The results have significant implications for both academics and business practitioners. Academically, the study contributes to the understanding of VLGC market interactions which have not be investigated in the literature. SEM is a comprehensive approach to test shipping market relationships. By identifying the direct and indirect relationships between variables, the study provides a holistic picture of the VLGC market mechanism. For industrial players, including shipowners, knowing the market interactions will aid their decision-making process, including freight rate movement and ship investment. For example, the key factor influencing freight rates is market pressure. Shipowners should pay attention to LPG export volume from key exporting areas as well as fleet size growth to identify the direction of freight movement. The increase of global ton-mile demand relies heavily on US LPG production and export capacity, while Middle East exports have remained relatively stable during the past few years. Moreover, shipowners and investors planning to acquire new VLGC tonnage, they should take note that the price of the vessel, no matter new or old, is the reflection of the current freight level and that it is wiser to place a new order if they anticipate strong seaborne trade volume growth in the future.

4.2 Dynamic relationships between LPG freight rate, crude oil price and LPG product price spread: a copula-GARCH approach

The freight market could be influenced by a series of factors, such as aggregated global LPG demand and LPG fleet size, notably, also location price spread, which has been valued by industry practitioners, however, seldom been studied in the academic field. The oil price effects on LPG freight rate are also of interest but have always been ambiguous and have not been investigated thoroughly.

A location price arbitrage is a trading strategy to profit from market inefficiencies in price differences of a given commodity at different geographical locations. In the commodity markets, some empirical evidence from past studies has shown the existence of temporary market inefficiency and thus offers profitable trading opportunities for arbitrageurs and traders (Fanelli, 2015). Such arbitrage opportunities usually arise due to regional supply and demand imbalances, regulatory changes and some market distortions (Alizadeh and Nomikos, 2004). Spatial arbitrage enables buying from underpriced places and selling to overpriced markets to take advantage of price differentials. It is stated that global arbitrage plays create a dynamic trading environment for products. A location price spread is the commodity price difference between two locations. An arbitrage is considered open when the price spread between the same commodity in two different locations (A and B) is greater than the full cost of transportation (including freight cost and terminalling fee) required to transport it between A and B. See for example, Argus reported in Apr 2015 that Asian LPG buyers taking US cargoes could make a profit of $35/t, taking into account cost of transportation. The arbitrage window was opened due to softening freight rate caused by vessel availability and weaker spot cargo prices at LPG export terminals near Houston (Argus, 2015). In fact, IHS publishes Waterborne LPG report every month showing the world LPG trade economics. From the US to Asia, based on IHS, the US-Asia arbitrage is calculated as (Propane CIF Japan market price – propane FOB US Gulf Coast price – source terminalling – VLGC freight cost). The LPG location price spread could affect the LPG shipping freight market via two channels: willingness to pay for shipping and ton-mile demand. When the location price spread is high, traders will profit more from the price spread and thus have more money to pay to shipowners, which leads to an increase in the freight rate. Meanwhile, the wide price spread would incentivize traders to move more cargoes, which creates more ton-mile demand, and these cargoes would compete for limited vessel spaces, thus drive up shipping freight rate. On the other hand, when the price spread narrows and makes no economic profit to move the cargo, companies would rather pay a cancellation fee to cancel the contract instead of moving it at a larger loss. This happens more often in the US where cargo cancellation is allowed, whereas, it is prohibited in the Middle East. Therefore, demand for LPG transportation, especially in the US, would be much influenced by the arbitrage economics. Such demand will then have an impact on the VLGC freight rate. For instance, as reported by Tradewinds (2016), the weakness in VLGC spot rates experienced in the first half 2016 was mainly attributed to the tighter propane differentials.

One distinguishing feature of the LPG shipping market is that there are often energy substitutes for LPG products, such as naphtha (Engelen and Dullaert, 2012). They could both be used as petrochemical feedstock. Thus, this makes shipping demand for LPG elastic, especially in the petrochemical sector, and very much dependent on the LPG-naphtha spread as well as LPG arbitrages between different locations. This brings up the question of how crude oil prices affect the arbitrage economics and overall VLGC freight rates. LPG such as propane and butane are related to the oil market both on the supply side (product of crude refining process) and demand side (through its use for fuel and heating). Oil prices have historically been the main driver for LPG prices (Oglend et al., 2015). Refined products are a derivative of the crude product and therefore, the refined and crude oil prices should be interrelated and have a long-run relationship.

Based on the literature review in Chapter 2, to the best of our knowledge, no study has been done to investigate the relationship between freight rate and the spatial price spread of the commodities carried by the ships. The existing literature focuses on information spillover effects between freight rates and the corresponding commodity prices (Haigh and Bryant, 2001; Yu et al., 2007).

Alizadeh and Nomikos (2004) relate the tanker freight rate formation to the differential of crude futures and physical prices, which reflects the cost of carry relationship. However, such an assumption was not supported by the statistical investigation. The reason they provide is the existence of arbitrage opportunities. To date, no study has considered the relationship between the freight rate and spatial price difference.

There has also been a handful of research analyzing the correlations between refined product prices and oil prices. Asche et al. (2003) have investigated the relationships between refined products and crude oil prices, using Johansen (1988) cointegration tests. Their findings suggested that a long-run relationship exists between crude oil prices and end products, with the exception of crude oil and heavy oil prices. Moreover, they found that crude oil prices could determine the refined product prices, however, it is not true in the other way around. This study has also suggested some market inefficiencies in relative pricings, which enable arbitrage profits to be taken. Specifically, regarding the relationship between LPG prices and oil prices, Oglend et al. (2015) have investigated the shale gas boom effect on the relationship between LPG and oil prices and concluded that LPG and oil price correlation has weakened in recent years due to shale gas revolution. Although spatial arbitrage has been an age-old concept for trading firms, little research has put emphasis on its importance. Pirrong (2014) concluded that commodity trading firms' primary function is to carry out physical arbitrages, which may add value through different transformation processes. Skadberg et al. (2015) studied the spatial arbitrage for US soybeans using stochastic optimization techniques and copula joint distributions.

Baltic LPG (BLPG), oil price and product price returns are identified to be skewed and leptokurtic (Goulielmos & Psifia, 2007; Reboredo, 2011). As a consequence, linear and other traditional models are not suitable for modeling freight, oil and product price distributions. Furthermore, they may demonstrate asymmetric or tail dependence behaviors, which make conventional multivariate GARCH models unsuitable. Therefore, this study proposes a dynamic conditional copula-GARCH approach to model the dependency between BLPG, Brent, and Propane price spread returns. Specifically, a univariate GARCH process is employed to model the marginal time series and a copula function is specified to model the dependence structure. Copula method compared to traditional multivariate time series analysis has several advantages. Firstly, copula-based models provide more flexibility in modeling multivariate distributions, allowing researchers to separately specify the models for the marginal distributions and the dependence structure that combines them to form a joint distribution. The copula approach to formulate multivariate distributions is particularly beneficial when the marginals are complex and cannot simply extend to a multivariate situation (Liu and Luger, 2009). Secondly, copula functions could capture a wide array of dependence structures, including nonlinear, asymmetric and tail dependence. Some time series analyses showed the benefits of copula-GARCH models (Patton, 2006; Hu, 2006; Jondeau and Rockinger, 2006; Rodriguez, 2007; Liu and Luger, 2009).

The objective of this section is to examine the dependency structure between VLGC freight rates and LPG location price spread, VLGC freight rates and Brent crude oil price, as well as the dependency structure between Brent crude oil and different propane prices and how that affects the commodity price spread level. A conditional copula-GARCH model is employed with the dependency both rendered constant and time-varying.

4.2.1 Data and Descriptive Statistics

4.2.1.1 Data

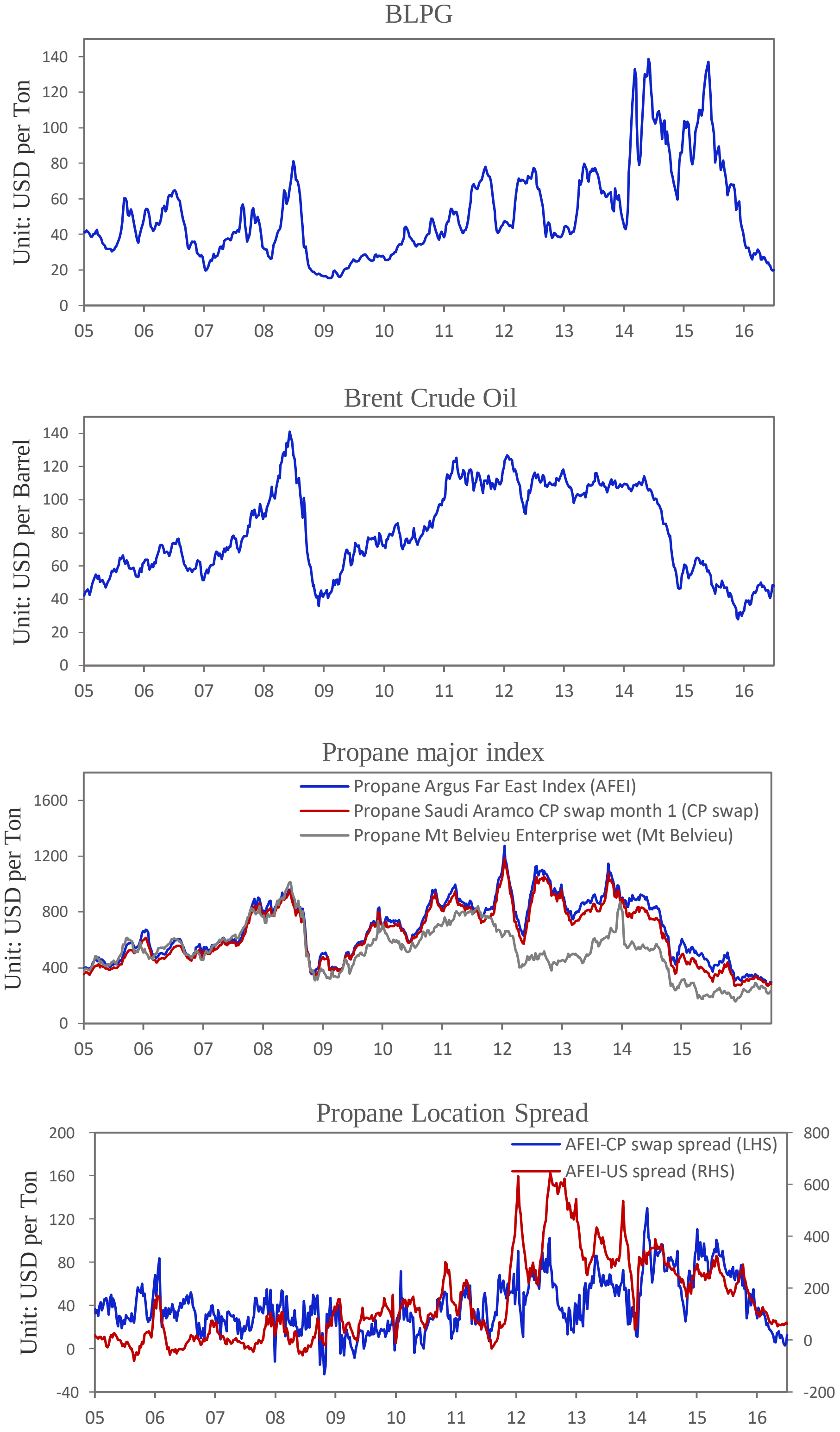
Our dataset consists of weekly average BLPG freight rate for the transportation of 44,000 metric tons of LPG from Ras Tanura, the Middle East to Chiba, Japan, which is obtained from Baltic Exchange. In addition, we obtain weekly average prices of Brent physical and three propane prices, including Mt Belvieu, Saudi Aramco CP swap and Argus Far East Index (AFEI) for the period 2 January 2005 to 22 August 2016 (600 observations), which are obtained from Datastream and Argus. The location price spread between the Middle East and the Far East (AFEI- CP swap) is calculated by taking the difference between AFEI and Saudi Aramco CP swap price, while the price spread between the US and the Far East (AFEI-US) is estimated by the difference between AFEI and Mt Belvieu price.

The original data are transformed into the logarithm ratio which could reflect the level of price changes, by taking the logarithm difference of the two successive weekly prices. One issue is that the location spread may not be always positive. To handle the negative values appeared in some product spread series, one common practice is to add a constant value to AFEI-CP swap and AFEI-US series prior to applying the log transform (Osborne, 2011). Therefore, the transformation becomes $\log(X + a)$, where X is the original value in the data series and a is a constant. a is chosen to ensure that $min(X + a)$ is a very small positive number. It is noted that adding a small constant will result in a slightly different return set. An alternative would be to truncate all negative data. However, it will result in important information loss.

4.2.1.2 Summary of descriptive statistics

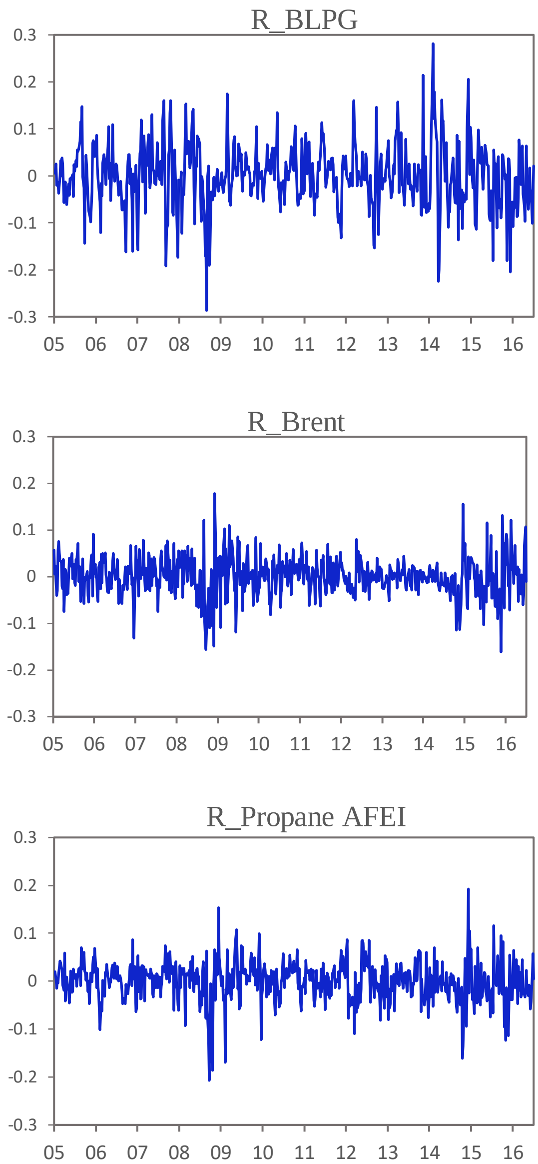
The graphs in Figure 4.5 show the price developments of the BLPG freight rate, Brent crude, Propane Argus Far East Index (AFEI), Propane CP swap month 1 and Propane Mt Belvieu prices, as well as the AFEI-CP swap and AFEI-US price spreads. The AFEI-CP swap spread has been almost all times positive, due to the lower price the Middle East offers as a low-cost region. However, the AFEI-US spread fluctuated around zero in the past and has become always positive since 2012 on the back of shale gas revolution which makes the US a cost competitive region and thus lowers the Mt Belvieu propane prices significantly. The spread between AFEI and Mt Belvieu has reached even 600 dollars per ton in 2012. The widely-open arbitrage has made exports from the US possible and economical. US exports surged with the new export terminals coming online since 2013. The return series are also plotted as shown in Figure 4.6. At a first glance, we could see that the weekly returns for BLPG are highly volatile. The volatilities are higher during the 2007-2008 global financial crisis and after 2014, when crude oil prices fall sharply. Similar patterns are observed in Brent oil price and also propane price volatilities. There are also volatility clustering effects (high volatility followed by high volatility, low volatility followed by low volatility) for all return series, justifying the use of GARCH models.

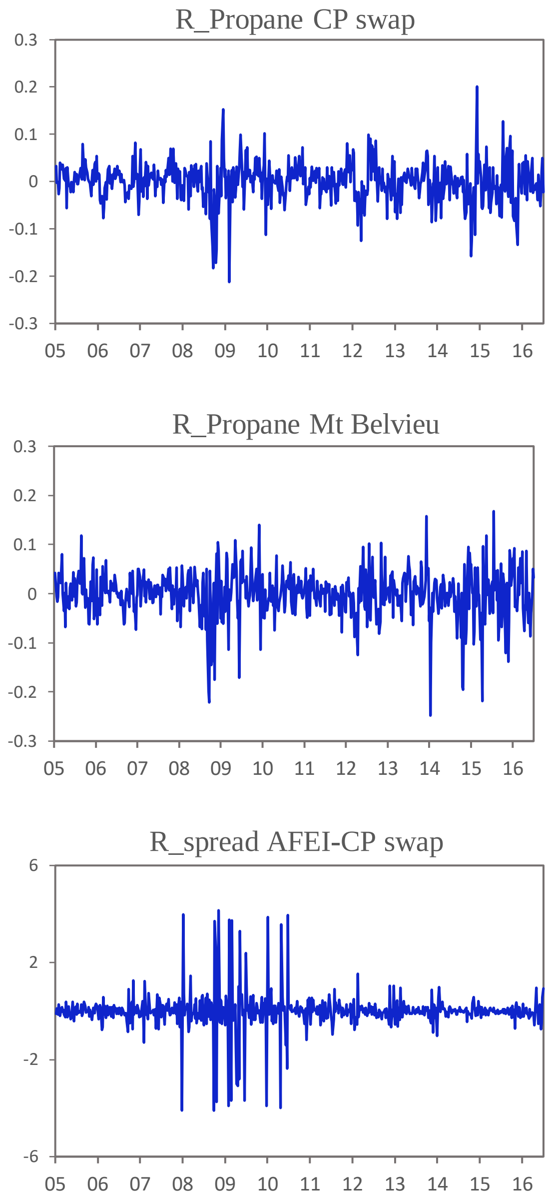
Figure 4.5 Price developments of major indices



Source: drawn by author based on Baltic Exchange, Datastream and Argus.

Figure 4.6 Weekly returns of major index





Source: Author.

Table 4.6 summarizes the descriptive statistics for all return series during sample period 2005-2016. Jarque-Bera test suggests the rejection of the normality assumption. All seven series exhibit negative skewness (except AFEI-Mt Belvieu swap price spread) and kurtosis that is higher than normal. The negative skewness indicates that negative returns occur more often than large positive returns. The excess kurtosis suggests that all return pairs have high peaks and fat tails. Hence, it is more suitable to use skewed Student-t distributed error terms in the AR-GARCH models. Ljung-Box (LB) Q-statistic is conducted for the autocorrelation test and the test results as shown in Table 4.6 suggest that the null hypothesis of non-correlation are all rejected at 1% level and all series demonstrate significant autocorrelation. As such, an autoregressive process would be appropriate. Finally, statistics from ARCH-LM test for heteroskedasticity indicate that all return series exhibit ARCH effects.

Table 4.6 Descriptive statistics for return series

	R_BLPG	R_BRENT	R_PAFEI	R_PCPS	R_PMB	R_AFEICPS	R_AFEIUS
Mean	-0.001192	0.000223	-0.000456	-0.000368	-0.000758	-0.001144	-0.019708
Maximum	0.281285	0.178138	0.192454	0.201042	0.167710	4.148952	5.515182
Minimum	-0.286632	-0.161312	-0.207100	-0.212258	-0.247897	-4.096685	-5.082301
Std. Dev.	0.066795	0.041924	0.041776	0.040992	0.048656	0.787722	1.124940
Skewness	-0.077910	-0.102333	-0.480001	-0.521343	-0.897356	-0.098994	0.014222
Kurtosis	1.654182	1.778274	3.111913	3.832484	3.712986	14.918946	10.039401
Jarque-Bera	70.31**	81.54**	268.44**	398.90**	429.76**	5610.1**	2541.7**
Q (5)	205.04**	34.25**	94.28**	107.63**	50.74**	68.53**	18.16**
Q (10)	209.99**	46.21**	108.37**	118.71**	70.84**	84.84**	28.29**
ARCH-LM (12)	79.3**	83.8**	99.3**	130.8**	121.9**	146.8**	175.7**
AR (p)	2	1	1	1	1	1	1

** indicate significance at 1% level, * indicate significance at 5% level. Ljung-Box (LB) Q-statistic is the test for autocorrelation, conducted using 5 and 10 lags. ARCH–LM is the heteroscedasticity test, conducted using 12 lags. AR (p) indicates the best AR lag selected by BIC criterion.

Source: Author.

4.2.2 Results and Discussions

4.2.2.1 Marginal estimation results

The marginals need to be correctively specified before using copula methods for dependence measure. The AR-GARCH (1, 1) model is one of the most common and popular models to describe financial time series (Diebold et al., 1998). As shown in Section 4.2.1.2, all series exhibit autocorrelation and GARCH effects, which justify the use of the AR-GARCH model. The optimal AR (p) lags are determined by the BIC criterion as shown in the last column of Table 4.6.

One important condition for conditional copulas to work based on Sklar's theorem is that they must be conditioned with the same information set. Thus, cross variable relationships are tested to identify the potential serial dependency between one series and the lagged value of another series. Based on Patton (2013), Newey-West adjusted regressions are performed between pair-wise variables by regressing the residuals from one series based on optimal AR lags in Table 4.6 and the lagged values of other series. Chi-squared tests are then performed. The null hypothesis is that all parameter estimates are zero. Insignificant p-values indicate no significant cross-equation lags exist between the series. As can be seen from Table 4.7, only three out of twelve pairs have significant cross-variable relationships at 5% significance level with a lag order of 5. The rests are insignificant. For model parsimony and comparability concern, a more complicated marginal specification for the three pairs is not adopted in this study. Therefore, the marginals estimated from AR-GARCH model are used directly for second step conditional copula building.

Table 4.7 Cross-equation relationship analysis for the residuals from AR models

Pairs	BLPG-AFEI-CP Swap	BLPG-AFEI-US	Brent-AFEI	Brent-CP Swap	Brent-MB	BLPG-Brent
Chi-sq p-value	0.8499	0.0162*	0.3719	0.5102	0.0368*	0.0707
Pairs	AFEI-CP Swap-BLPG	AFEI-US-BLPG	AFEI-Brent	CP Swap-Brent	MB-Brent	Brent-BLPG
Chi-sq p-value	0.0580	0.6646	0.0443*	0.2035	0.6258	0.3885

Newey-West adjusted heteroscedastic-serial consistent Least-squares Regression is used for serial correlation test, conducted with an order of 5. P-values for chi-squared test are provided. * indicate significance at 5% level, ** indicate significance at 1% level.

Source: Author.

The corresponding skewed-t AR (p) - GARCH (1, 1) parameters for each return series are calculated in Table 4.8 below.

Table 4.8 Parameter estimates for the marginal models

	R_BLPG	R_BRENT	R_PAFEI	R_PCPS	R_PMB	R_AFEICPS	R_AFEIUS
Mean equation							
μ	0.004286 (0.004227)	0.000452 (0.00186)	0.002103 (0.002381)	0.002172 (0.002271)	0.001869 (0.002035)	-0.013597 (0.007220)	-0.018196** (0.006430)
θ_1	0.684445** (0.043175)	0.216638** (0.041127)	0.27386** (0.046067)	0.224627** (0.043361)	0.183319** (0.035361)	-0.248232** (0.032891)	0.055736 (0.044397)
θ_2	-0.186916** (0.034916)						
Variance equation							
ω	0.00043** (0.000135)	0.000012 (0.000009)	0.000123** (0.000038)	0.000085** (0.000028)	0.000097 (0.000058)	0.022065 (0.016464)	0.004747** (0.001443)
α	0.32312** (0.068351)	0.080989** (0.026134)	0.142208** (0.044815)	0.141833** (0.041868)	0.147064* (0.059314)	0.524826** (0.082330)	0.495515** (0.067739)
β	0.596385** (0.069903)	0.916375** (0.016263)	0.783378** (0.049704)	0.811238** (0.040261)	0.818494** (0.069311)	0.474174 (0.125789)	0.503485** (0.041366)
υ	5.35548** (1.291324)	8.545405** (2.844844)	7.436142** (2.058835)	5.677401** (1.423702)	5.464183** (1.255305)	2.706052** (0.422063)	3.264051** (0.249816)
λ	1.110077** (0.064565)	1.021729** (0.056621)	0.95348** (0.053712)	0.966654** (0.048978)	0.903584** (0.058987)	0.858922** (0.040273)	0.877256** (0.037715)
Q (5) p -value	0.8746	0.8921	0.9999	0.4971	0.1878	0.8465	0.5715
Q^2 (5) p- value	0.4597	0.4173	0.9795	0.8353	0.3513	0.9947	0.9193
ARCH-LM(5) p-value	0.5890	0.1182	0.9923	0.8761	0.0756	0.9715	0.7391

Based on equations (3.26) and (3.27). The parameters are estimated using maximum likelihood method. The numbers in parentheses are standard deviations. Ljung-Box (LB) Q-statistic and Q^2-statistics are the test for autocorrelation, conducted using 5. ARCH–LM is heteroscedasticity test, conducted using 5 lags. * indicate significance at 5% level, ** indicate significance at 1% level.

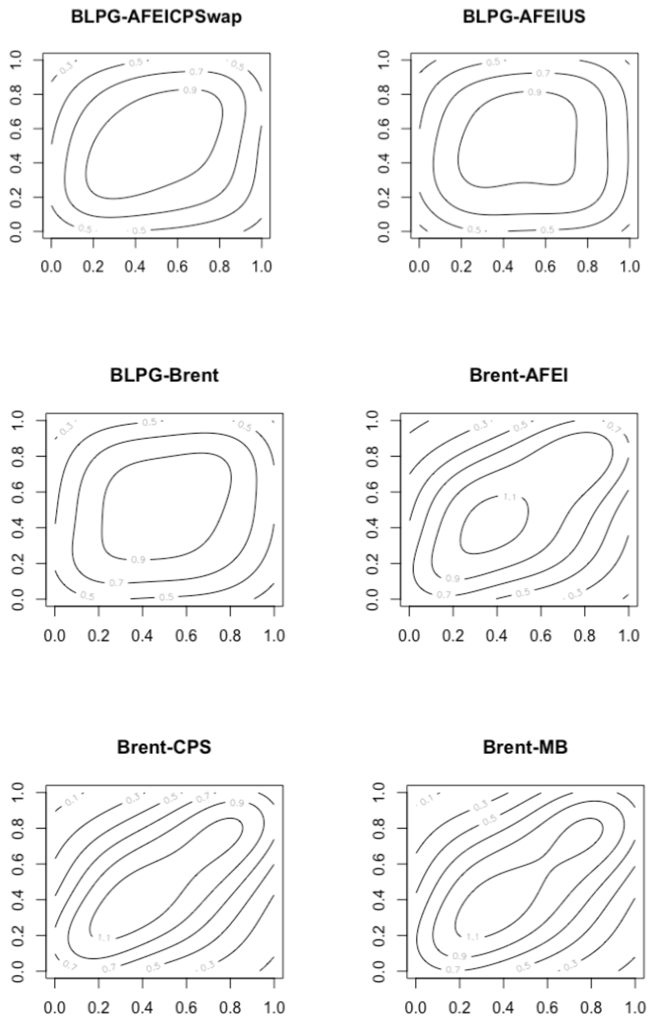
Source: Author.

As indicated in Table 4.8, skewness and shape parameters are all significant, justifying the skewed-t distribution of error term. In the GARCH model, the parameters α and β are significant for all series and as such explain that both BLPG, Brent crude oil, different propane prices and two propane location spread returns have volatility clustering effects. As $\alpha + \beta$ is close to 1, this indicates that shocks are quite persistent to all return series. As mentioned, the marginal distributions need to be correctly specified for next step dependence measures. The Ljung-Box (LB) Q and Q^2 tests, as well as ARCH-LM test are performed for the standardized residuals to check if the marginals are modeled properly. As shown in Table 4.8, all Q, Q^2 and ARCH-LM statistics are not significant, indicating that there are no remaining autocorrelation and GARCH effects unexplained by the model. Thus, the marginals are properly specified.

4.2.2.2 Copula results

Before fitting into different copula types, the contour plots of the distribution generated by empirical copulas are presented first (Figure 4.7) to visualize how the dependency structures would look like between different filtered series. At a first glance, the asymmetric tail dependence is not very obvious for BLPG and propane AFEI - Mt Belvieu spread and BLPG-Brent pairs, while being more noticeable between BLPG and propane AFEI - CP swap spread. Next, both constant and time-varying copulas are fitted to the residuals from marginals.

Figure 4.7 Empirical copula contour plots



Source: Author.

The estimated parameters of constant and time-varying dependence between different return series are presented in Table 4.9 and 4.10. The standard errors are obtained from copula parameters, which do not take into account the estimation error from marginal distributions. Alternatively, bootstrap or simulation method for standard errors of the two-staged parameter estimator as discussed by Patton (2013) can be used. The copulas for each pair are ranked based on both Log-likelihood and AIC criterion. The AIC results are all consistent with the Log-likelihood results. Cramer-von Mises tests are used to get an additional confirmation of goodness-of-fit as shown in Table 4.11. The test statistic measures the distance between the fitted copula $C_k(u_t, v_t; \hat{k})$ and the empirical copula C_n, and is given by:

$S_n = \sum_{t-1}^{n}\{C_k(u_t, v_t; \hat{k}) - C_n(u_t, v_t)\}^2$. A parametric bootstrap procedure is used to compute the p-value of the test (Genest et al., 2009). The large p-value indicates that the copula provides a better fit to the model (Aloui et al., 2013). The CvM tests provide mostly consistent results as AIC and Log-likelihood values.

Among constant copulas, the best-fitted copulas for each pair all have insignificant p-value from CvM test, indicating the good fit of the model. By AIC criterion, time-varying copulas perform better for all the return series except for BLPG and AFEI-US pair, indicating significant conditional time-varying characteristics of the dependency structure between most of the pairs. The different dependence structures are elaborated in the following sections.

Table 4.9 Estimates for constant copula models

	BLPG-AFEI-CP Swap	BLPG-AFEI-US	Brent-AFEI	Brent-CP Swap	Brent-MB	BLPG-Brent
Gaussian						
ρ	0.105** (0.0268)	0.0292 (0.0294)	0.555** (0.0122)	0.625** (0.00996)	0.589** (0.0111)	0.104** (0.0269)
LL	3.23	0.25	107.89	145.76	125.18	3.12
AIC	-6.46	-0.50	-215.78	-291.52	-250.36	-6.24
Student-t						
ρ	0.115** (0.0433)	0.0316 (0.0423)	0.552** (0.0279)	0.628** (0.0246)	0.593** (0.0247)	0.107** (0.0424)
v^{-1}	0.010 (0.0420)	0.010 (0.0479)	0.088 (0.0526)	0.145** (0.0515)	0.069 (0.0425)	0.046 (0.0429)
LL	3.67	0.05	109.5	150.91	126.74	3.69
AIC	-7.33	-0.09	-218.99	-301.81	**-253.47**	-7.37
Clayton						
θ	0.116** (0.0307)	0.015 (0.0277)	0.827** (0.0952)	1.050** (0.161)	0.927** (0.119)	0.127** (0.0311)
LL	2.6	0.05	85.02	114.84	98.62	3.55
AIC	-5.20	-0.10	-170.04	-229.68	-197.24	-7.10
Gumbel						
θ	1.060** (0.0308)	1.000** (0.0278)	1.530** (0.0585)	1.70** (0.0683)	1.60** (0.0625)	1.050** (0.0305)
LL	1.89	-5.83	100.87	140.48	113.6	1.74
AIC	-3.78	11.66	-201.74	-280.96	-227.20	-3.48
Frank						
θ	0.799** (0.244)	0.239 (0.229)	3.670** (0.481)	4.650** (0.67)	4.280** (0.589)	0.676** (0.240)
LL	5.14	0.48	93.35	136.36	120.77	3.72
AIC	**-10.28**	**-0.96**	-186.70	-272.72	-241.54	**-7.44**
Joe						
θ	1.050** (0.0356)	1.000** (0.0331)	1.690** (0.0751)	1.900** (0.091)	1.760** (0.0805)	1.040** (0.0353)
LL	0.63	0.00	79.11	111.52	86.41	0.62
AIC	-1.26	0.00	-158.22	-223.04	-172.82	-1.24
Survival Clayton						
θ	0.095** (0.0301)	0.00945 (0.0276)	0.828** (0.0954)	1.050** (0.163)	0.892** (0.11)	0.008** (0.0296)
LL	1.81	0.02	85.04	117.53	93.85	1.36
AIC	-3.62	-0.04	-170.08	-235.06	-187.70	-2.72
Survival Gumbel						
θ	1.070** (0.0318)	1.000** (0.0278)	1.530** (0.0583)	1.70** (0.0682)	1.610** (0.0629)	1.060** (0.0313)
LL	3.67	-6.88	101.05	140.15	117.94	2.85
AIC	-7.34	13.76	-202.10	-280.30	-235.88	-5.70
BB1						
δ	0.091 (0.0744)	0.0139 (0.0618)	0.338** (0.086)	0.366** (0.091)	0.363** (0.0903)	0.119 (0.0662)
θ	1.02** (0.0398)	1.000** (0.0365)	1.350** (0.0603)	1.470** (0.0697)	1.390** (0.065)	1.010** (0.0332)
LL	2.72	0.05	110.29	150.25	123.51	3.57
AIC	-5.43	-0.09	-220.57	-300.49	-247.01	-7.13
Survival BB1						
δ	0.0081 (0.0648)	0.00826 (0.0676)	0.346** (0.0863)	0.398** (0.0921)	0.313** (0.0879)	0.00808 (0.0606)
θ	1.07** (0.0401)	1.001** (0.0404)	1.340** (0.0597)	1.450** (0.0693)	1.420** (0.0666)	1.060** (0.0376)
LL	3.68	0.00	110.68	151.42	125.24	2.85
AIC	-7.35	0.01	**-221.35**	**-302.83**	-250.47	-5.69
BB7						
δ	1.01** (0.0484)	1.000** (0.0473)	1.460** (0.0779)	1.610** (0.0887)	1.480** (0.0838)	1.000** (0.0402)
θ	0.115 (0.0622)	0.0145 (0.0516)	0.597** (0.0855)	0.740** (0.0967)	0.670** (0.0916)	0.127* (0.0564)
LL	2.60	-1.21	109.48	147.09	119.02	3.55
AIC	-5.19	2.43	-218.95	-294.17	-238.03	-7.09

Based on equations (3.7) to (3.15). Standard errors are in parenthesis. log-likelihood and AIC value for different specifications for each pair are reported. The minimum AIC value is in bold. The AIC criterion is used to evaluate the goodness of fit of the selected models. ** indicates significance at 1% level and * indicates significance at 5% level. LL stands for Log-Likelihood.

Source: Author.

Table 4.10 Estimates for time-varying copula models

	BLPG-AFEI-CP Swap	BLPG-AFEI-US	Brent-AFEI	Brent-CP Swap	Brent-MB	BLPG-Brent
Time-varying Gaussian						
ω	0.031* (0.0144)	0.0485* (0.0181)	2.277** (0.5787)	1.468** (0.0632)	-0.138** (0.051)	0.01 (0.0119)
α	0.086 (0.0509)	0.0751 (0.1784)	0.269 (0.1493)	-0.002 (0.1998)	0.123** (0.0406)	-0.037 (0.0292)
β	1.659 (0.1434)	0.330 (0.6337)	-2.114 (1.117)	0.004 (0.0998)	2.433** (0.1234)	1.957** (0.0858)
LL	4.63	0.32	108.48	145.77	131.76	4.18
AIC	-9.25	**-0.63**	-216.95	-291.52	-263.51	-8.35
Time-varying SJC						
ω_U	-17.189** (0.1035)	-13.731** (0.0044)	-0.613* (14.683)	-2.003** (0.2459)	-0.531 (0.6294)	-15.737** (0.0357)
α_U	-2.741** (0.0023)	-0.6597 (0.0000)	1.87 (19.2648)	1.414* (0.6929)	-2.915 (1.8394)	-3.207** (0.0069)
β_U	-0.009** (0.0000)	-0.0019 (0.0000)	-0.984* (52.3539)	3.339** (0.5741)	1.530 (0.963)	-0.008** (0.000)
ω_L	3.688** (0.0000)	-23.2374** (0.0135)	3.548** (0.3322)	0.749** (0.137)	0.670** (0.1286)	-13.216** (0.0001)
α_L	-24.999** (0.002)	-4.2855 (0.0019)	-13.631** (1.1359)	-5.195** (0.4719)	-7.471** (0.4911)	24.993** (0.0002)
β_L	-7.559** (0.0000)	-0.0117 (0.0000)	-4.456** (0.0577)	-0.230* (0.0800)	0.831** (0.114)	4.538** (0.000)
LL	4.19	-1.19	113.59	151.08	130.72	4.35
AIC	-8.36	2.40	**-227.17**	-302.15	-261.42	-8.69
Time-varying Student-t GAS						
ω	0.0185** (0.0008)	0.015** (0.0008)	0.316 (0.1781)	0.557 (0.3907)	0.018 (0.0794)	0.010** (0.0011)
α	0.0769** (0.0128)	0.0224** (0.0027)	0.067 (0.0664)	0.171* (0.0841)	0.066 (0.0386)	-0.045** (0.0076)
β	0.9225** (0.0326)	0.800** (0.0396)	0.745** (0.146)	0.621* (0.2605)	0.987** (0.0757)	0.957** (0.000)
υ^{-1}	0.050** (0.0056)	0.01** (0.0000)	0.084 (0.0562)	0.126* (0.0621)	0.051* (0.0258)	0.05** (0.0065)
LL	5.84	0.07	110.77	153.13	140.72	5.24
AIC	-11.66	-0.13	-221.52	**-306.25**	**-281.43**	**-10.47**
Time-varying Rotated Gumbel GAS						
ω	-0.038 (0.0326)	-0.072 (0.1047)	-0.057 (0.0739)	-0.116 (0.1259)	-0.006 (0.0706)	-0.149 (0.0888)
α	0.159* (0.0663)	0.051 (0.1568)	0.07 (0.1371)	0.141 (0.1429)	0.085 (0.2861)	-0.243 (0.1925)
β	0.989** (0.0108)	0.981** (0.0408)	0.984** (0.0289)	0.697* (0.3475)	0.989** (0.1067)	0.951** (0.041)
LL	7.57	-0.44	101.62	141.87	129.91	4.38
AIC	**-15.13**	0.88	-203.22	-283.73	-259.82	-8.75

Based on equations (3.16) to (3.23). Standard errors are in parenthesis. log-likelihood and AIC value for different specifications for each pair are reported. The minimum AIC value is in bold. The AIC criterion is used to evaluate the goodness of fit of the selected models. ** indicates significance at 1% level and * indicates significance at 5% level. LL stands for Log-Likelihood.

Source: Author.

Table 4.11 P-value for CvM goodness-of-fit test

	BLPG-AFEI-CP Swap	BLPG-AFEI-US	Brent-AFEI	Brent-CP Swap	Brent-MB	BLPG-Brent
Gaussian	**0.210**	**0.740**	0.030	**0.330**	**0.140**	**0.420**
Student-t	**0.213**	**0.589**	0.025	**0.391**	**0.064**	**0.817**
Clayton	**0.090**	**0.189**	0.000	0.000	0.000	**0.758**
Gumbel	**0.081**	**0.449**	0.000	0.020	0.000	**0.094**
Frank	**0.760**	**0.780**	0.000	0.000	0.010	**0.650**
Joe	0.010	**0.263**	0.010	0.010	0.010	0.000
Survival Clayton	**0.071**	**0.204**	0.000	0.000	0.000	**0.053**
Survival Gumbel	**0.273**	**0.283**	0.000	0.000	0.000	**0.392**
BB1	**0.100**	**0.490**	**0.080**	**0.600**	0.040	**0.810**
Survival BB1	**0.220**	**0.250**	**0.090**	**0.990**	0.000	**0.230**
BB7	**0.110**	**0.340**	**0.210**	**0.160**	0.010	**0.770**

Insignificant p-values are highlighted in bold.

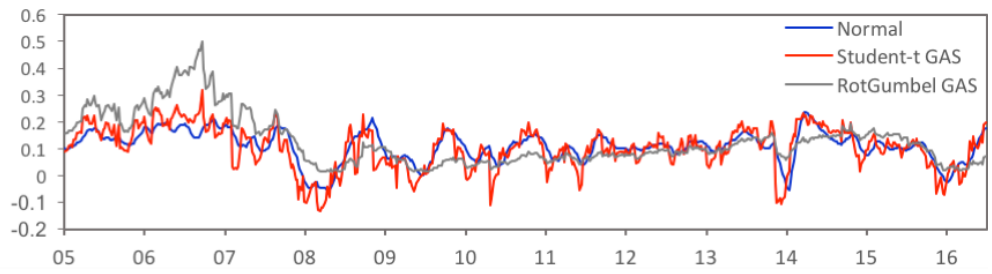
Source: Author.

Dependency between BLPG freight and location price spread

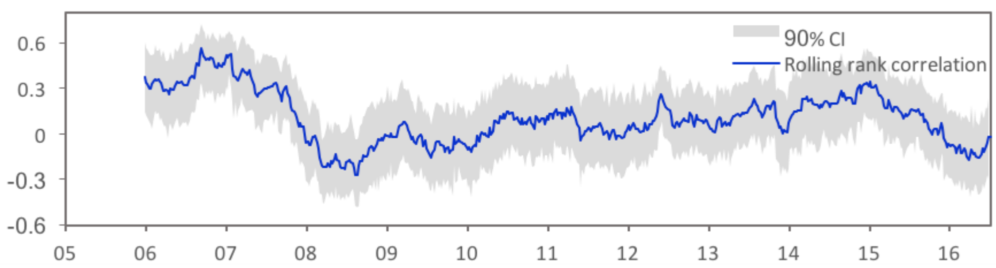
The dependency between BLPG and propane AFEI-CP swap spread could be best explained by time-varying Rotated Gumbel GAS copula. This result indicates that BLPG freight and the AFEI-CP swap spread seem to be more correlated in market downturns with time variations. The result is understandable as when the price spread shrinks sharply or even closes, the traders would have no extra money to pay for the shipowners and they would squeeze the cost for sea transportation, thus pushing down the freight rate. However, when the spread is widening, the benefits of arbitrage economics would not be shared equally with shipowners as the losses transferred in a market downturn. The average Kendall's τ rank correlation is around 0.1, which is a considered as a moderately weak relationship. Such a relationship becomes stronger in a market downturn as explained. The linear correlation implied by the time-varying Rotated Gumbel GAS copula as shown in Figure 4.8(a) is in line with the rolling window rank correlation computed based on residuals from the marginal models as Figure 4.8(b) shows.

Figure 4.8 Dependence estimates for BLPG-AFEI CPS based on time-varying copula and rolling window rank correlation

a. Conditional time-varying linear correlation from time-varying copulas



b. 52-week rolling window rank correlation

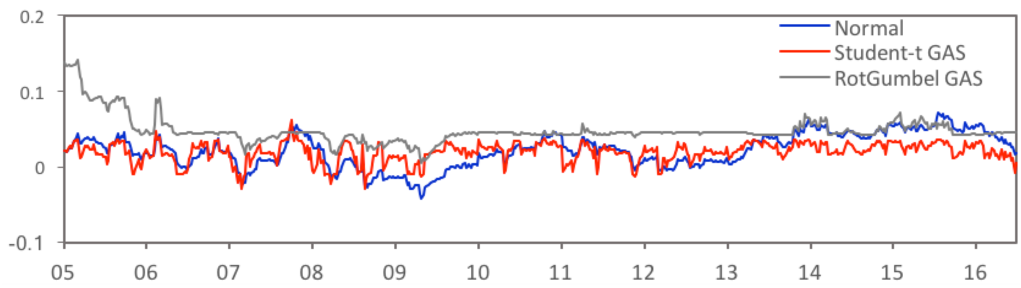


Source: Author.

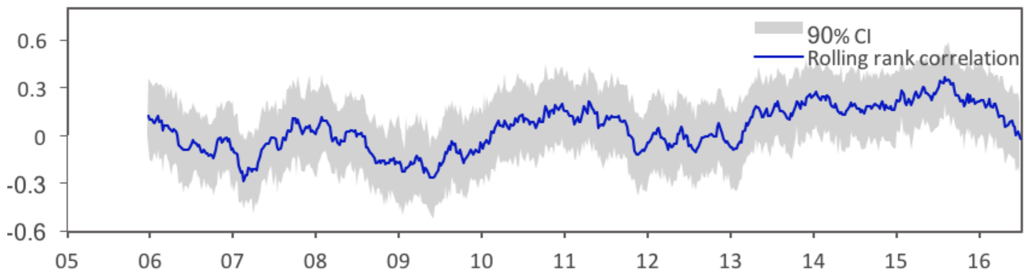
For the dependence between BLPG and propane AFEI-US spread, the constant frank copula is selected as the best-fitted one based on the AIC criterion, which is also confirmed by the CvM test. This indicates that the correlation between BLPG and AFEI-US is symmetric and has the same correlation across the entire distribution. Furthermore, the linear correlation implied by the constant normal copula is rather low, which is around 0.02. This implies that compared with the Middle East, the price difference effects between Asia and the US have limited impacts on the freight rate. This could be attributed to the traditionally dominant role the Middle East plays in the global LPG shipping market, compared to the US. The conditional linear correlation obtained from time-varying copulas is also plotted in Figure 4.9(a) together with rolling rank correlation (Figure 4.9(b)) to get a clear understanding of the dependence structure. The linear correlation from time-varying normal copula (the best fitted) indicates a stronger relationship between BLPG and AFEI-US spread since 2013. The correlation fluctuates around zero before 2013, then gradually increases to around 0.05 and stays above zero ever since. This is further evidenced by the rolling window rank correlation.

Figure 4.9 Dependence estimates for BLPG-AFEI US based on time-varying copula and rolling window rank correlation

a. Conditional time-varying linear correlation from time-varying copulas



b. 52-week rolling window rank correlation



Source: Author.

Dependency between crude oil price and propane product prices

The dependence structures between propane prices in different locations and the crude oil prices are examined to better understand how crude oil prices could affect the price spread. Time-varying copulas are selected for all three pairs: Brent-propane AFEI returns, Brent-propane Saudi Aramco CP swap returns and Brent-propane Mt Belvieu returns. However, the difference in LL value between the best fitted constant and time-varying copulas for Brent-AFEI, Brent-CP swap is very small (the difference being 6 and 3 respectively), while that for Brent-MB pair is much higher (difference=28), indicating possible higher time-varying dependence between Brent-MB. This, in fact, is confirmed in Figure 4.10 (a1, a2, a3). Figure 4.10 plots the time-varying linear correlation implied by time-varying copulas and rolling window rank correlation. Time-varying SJC copula provides the best fit for Brent-AFEI pair, while for Brent-CPS and Brent-Mt Belvieu pair, time-varying Student-t GAS copula is selected. For Brent-AFEI pair, the average tail dependence ($(\tau^U + \tau^L)/2$) and the difference in upper and lower tail ($\tau^U - \tau^L$)

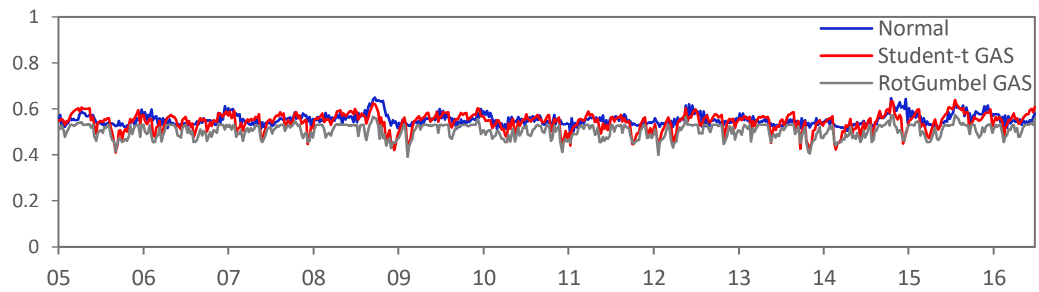
from time-varying SJC copula are shown in Figure 4.10(c1). The difference in upper and lower tail measures the degree of asymmetry. If the two series have symmetric tail dependence, the difference should be zero. As can be seen, the average tail dependence ranges from 0.2 to 0.5, while the difference in upper and lower tail fluctuates around zero in the range of (-0.4, 0.3). 67% of days the conditional upper tail dependence is larger than that of the lower tail. This implies that there is no persistent asymmetry dependency in one tail for Brent-AFEI pair. This is also evidenced by the difference in AIC and CvM test results. Although survival BB1 copula is selected for constant cases using AIC, BB7 is chosen by the CvM test.

Figure 4.10(a3) indicates clearly time-varying dependence features for Brent-Mt Belvieu pair from time-varying Student-t GAS copula (best-fitted copula). Same trend can be observed from the rolling window rank correlation (Figure 4.10(b3)). The correlation between Brent-propane prices maintained at a high level before 2010. However, such a relationship has become weaker since 2010 due to the shale gas boom and consequently more propane produced from natural gas production. This makes US propane price gradually decouple from crude oil prices and more related to natural gas prices (Oglend et al., 2015). However, the correlation increases significantly since the end of 2014, when crude oil prices collapse. The low crude oil prices have made natural gas not as profitable as before and put a break on the propane production from natural gas processing. Consequently, US propane price joins closely again with crude oil prices and the linear correlation ranges around 0.6 in this low oil price environment during 2015-2016. Nevertheless, the linear correlation implied by the constant Student-t copula could be regarded as the average of the time-varying correlations over the sample period. As it can be seen, the constant copula significantly overestimates the relationship during the shale gas boom period (2010-2014), while underestimates it after crude oil prices collapsed at the end of 2014.

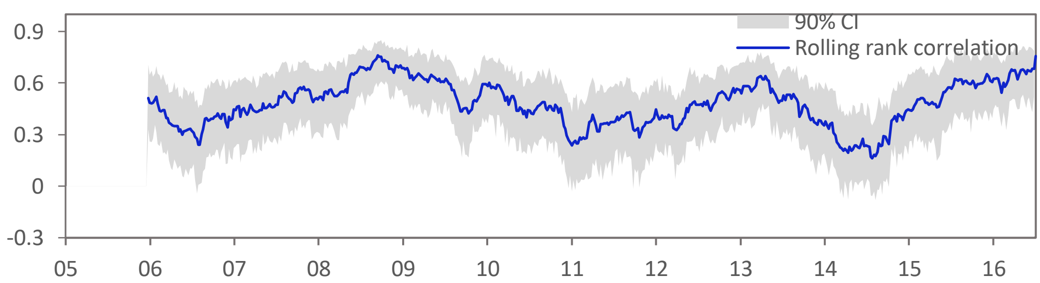
For constant copulas, survival BB1 copula provides the best fit for both Brent-AFEI and Brent-CP swap pairs. However, the LL differences between survival BB1 and Student-t copula for two pairs are very small. Brent-MB pair has symmetric tail dependence with Student-t copula selected for the constant case. Looking at the average linear correlation, the dependencies between different propane prices and the crude oil prices are all very strong. Furthermore, propane Saudi Aramco CP swap has the highest correlation with the crude oil prices (ρ = 0.625), followed by propane Mt Belvieu price (ρ = 0.589) and propane AFEI return (ρ = 0.555).

Figure 4.10 Dependence estimates for Brent and Propane prices based on time-varying copula and rolling window rank correlation

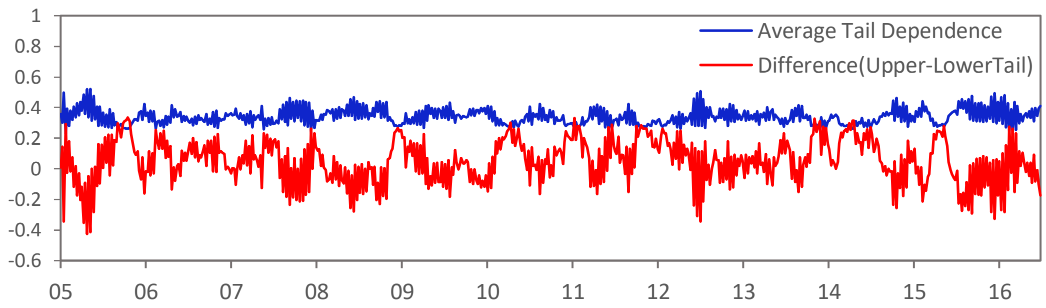
a1. Conditional time-varying linear correlation between Brent and Propane AFEI from time-varying copulas



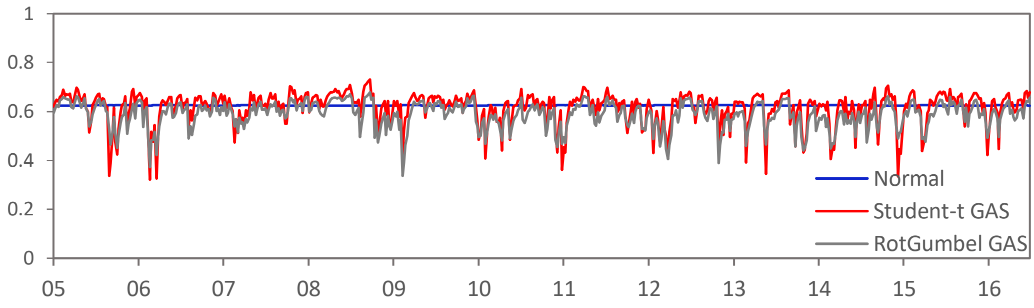
b1. 52-week rolling window rank correlation between Brent and Propane AFEI



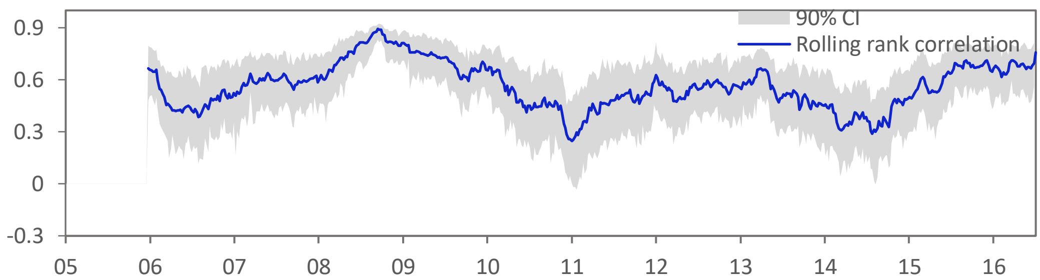
c1. Average conditional tail dependence and difference between upper and lower tail dependence between Brent and Propane AFEI from time-varying copulas



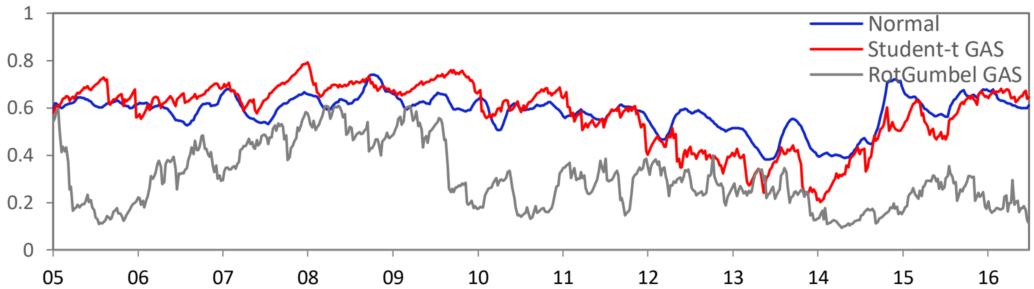
a2. Conditional time-varying linear correlation between Brent and Propane CP Swap from time-varying copulas



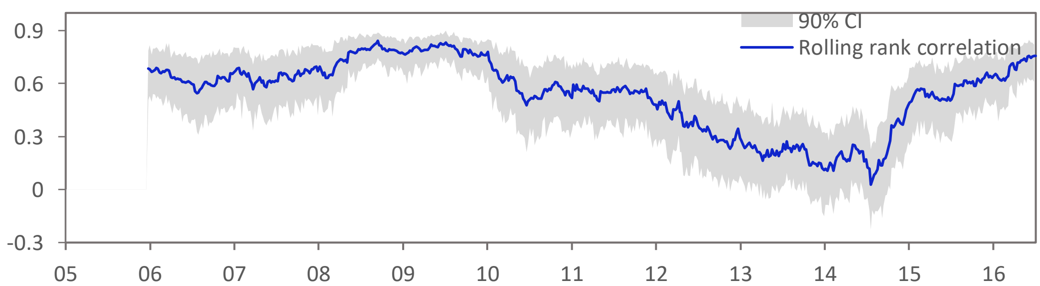
b2. 52-week rolling window rank correlation between Brent and Propane CP Swap



a3. Conditional time-varying linear correlation between Brent and Propane Mt Belvieu from time-varying copulas



b3.52-week rolling window rank correlation between Brent and Propane Mt Belvieu



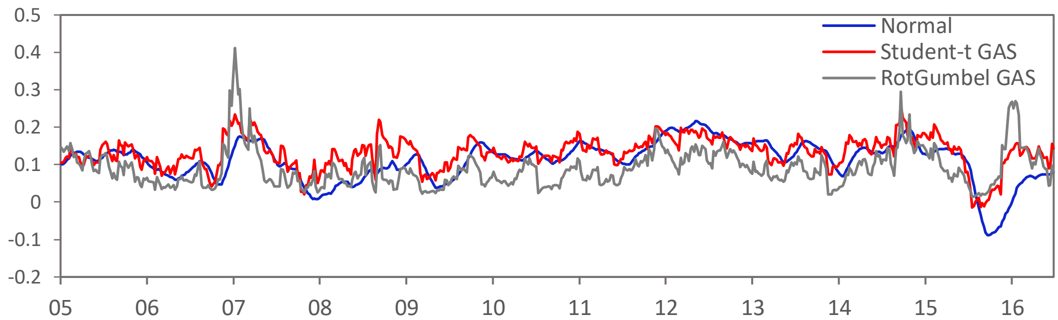
Source: Author.

Dependency between BLPG and crude oil prices

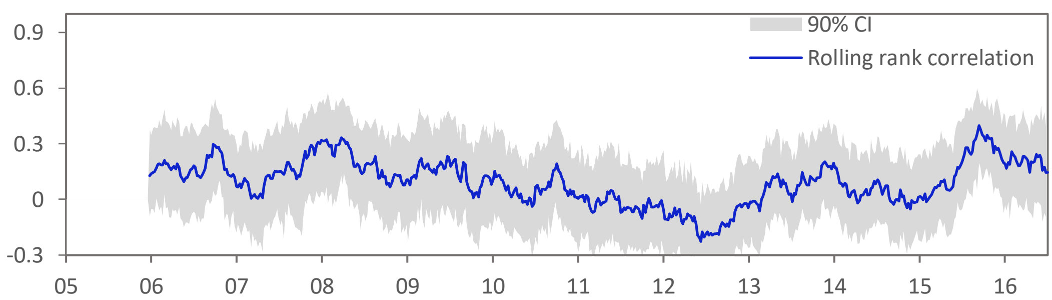
We further investigate the relationship between BLPG and crude oil prices. Results show that the time-varying Student-t GAS copula performs better than the rest, indicating a possible time-varying relationship. For constant cases, frank copula is selected by AIC, while Student-t copula has the largest p-value from CvM tests. This implies symmetric dependence between the two series. Furthermore, oil price effects on BLPG freight rate are modest at best, as indicated by Kendall's tau implied by Frank copula ($\tau = 0.1$). Figure 4.11(a) indicates the time-varying correlations implied by the time-varying copulas. As can be seen from best fitted Student-t GAS copula, the linear correlations increased to around 0.2 at the end of 2014, however, then dropped significantly since the end of 2015 and even turned negative for a short period amid a mild crude oil price recovery. Overall speaking, the dependency between BLPG and Brent is positive and tends to vary across time.

Figure 4.11 Dependence estimates for BLPG and Brent based on time-varying copula and rolling window rank correlation

a. Conditional time-varying linear correlation from time-varying copulas



b.52-week rolling window rank correlation



Source: Author.

4.2.2.3 Implications

The results as discussed above have several implications. Firstly, there exists a positive relationship between BLPG and AFEI-CP swap spread, and such dependency increases when a sharp drop in the price spread occurs. On the other hand, there observed to be a stronger relationship between BLPG and AFEI-US spread since 2013 on the back of the US shale gas revolution and increased LPG export. Furthermore, the dependency between BLPG and AFEI-CP swap spread has been higher than that between BLPG and AFEI-US spread, which is attributed to the much higher volume exported from the Middle East compared to the US. Secondly, in terms of the dependency between crude oil prices and different propane prices, there exist significant time-varying correlations between the US propane price and the crude oil prices, while the time variations in the dependency between propane Middle East and Far East price and the crude oil prices are less obvious. In addition, the linear correlations suggest that propane Middle East prices have the highest correlation with the crude oil prices compared to Far East propane prices. This suggests that an increase or decrease in the crude oil prices would cause a larger rise or drop in the propane Saudi Aramco CP prices than the AFEI price. The result is understandable as the Middle East is a key propane producing area, the propane price is linked more closely with its upstream oil price. On the contrary, Asia being an importing and consuming area, its propane price is affected by many other factors apart from oil price. Therefore, a drop in the crude oil prices would widen propane AFEI-CP price spread, thus leading to an increase in BLPG freight rate. As for the correlation between crude oil and AFEI-US spread, it differs in different time frames. For example, during the period around 2013, when the correlation between Brent crude and Mt Belvieu price drops below 0.4, which is lower than the correlation between Brent crude and AFEI price, any decrease in oil price would induce a larger drop in the AFEI propane price than Mt Belvieu price, thus narrowing the price spread. However, in a low oil price environment where the correlation between Brent crude and Mt Belvieu strengthens and becomes higher than that between Brent crude and AFEI price, a fall in oil price will actually widen the price spread. Therefore, there appears to be no definite answer regarding how crude oil affects the arbitrage economics between AFEI and US propane prices. However, it is more certain that in a low oil price environment like 2016, the crude oil price effects on the arbitrage economics, both AFEI-CP swap and AFEI-US spreads are negative. Indeed, we have observed a recovery in crude oil prices in the first half of 2016, in the meanwhile, a sharp drop in the location price spread.

Last but not least, when it turns to the overall dependency between crude oil prices and BLPG freight rate, it is positive for most of the times and they tend to co-move more in market downturns. As discussed previously, the crude oil price effects through arbitrage economics on BLPG freight are negative in a low crude oil price environment. However, considering the direct effects on the freight rate, the overall impact is positive, although relatively weak. This means that apart from influencing the arbitrage windows, crude oil prices play a different and much significant role in affecting the BLPG freight rate. For example, changes in crude oil prices would lead to changes in the seaborne transportation volume. On the one hand, a sharp drop in crude oil prices makes propane from NGL in the US unprofitable, thus leading to reduced volume exports. More specifically, the growth of export volume slows down, which lags behind the growth rate of VLGC fleets. Relatively less demand compared to the supply then causes a drop in the BLPG freight rate. In contrast, as it is known, Asia is a key demand center for crude oil. When the crude oil prices fall sharply, traders tend to bottom pick and buy more crude oil into Asia. As a result, oil refineries in Asia, especially China have to operate at high rates in order to utilize existing crude oil inventories in order to receive the next batch of crude oil. LPG comes out as a by-product and that results in higher LPG inventory level, which then contributes to less import demand. This again leads to reduced demand for sea transportation. Lastly, since LPG is often used as a petrochemical feedstock in the petrochemical industry and naphtha exists as its substitute, a sharp drop in crude oil prices would make naphtha more cost competitive compared to LPG, thus further dampens the LPG demand in the petrochemical use. Overall speaking, crude oil prices affect BLPG freight rate in different ways, both in terms of shipping demand and arbitrage economics. Overall speaking, the dependency between crude oil prices and BLPG freight rate is positive. However, we do observe some negative signs in the first half of 2016 as shown in Figure 4.11(a), indicating a possible higher weight of arbitrage economics playing on freight rate during this period.

The results provide significant implications for practitioners in the energy transportation field, including traders, charterers, and shipowners. By knowing the dependency structure between product price spread, crude oil prices, and freight rate, industrial players can anticipate fluctuations in the freight market when crude oil prices or product spreads change. It aids charterers for freight transportation budget planning and shipowners for revenue forecasting. For example, when the product price spread becomes less profitable, shipowners shall prepare for a drop in freight rate, consequently, a revenue squeeze.

4.3 A destination choice model for very large gas carriers (VLGC) loading from the US Gulf

Calls have been long made in the research community to improve the understanding of spatial patterns in seaborne energy transportation. Technological advances have opened the door to significant innovations in shipping behavior modeling, for example, the availability of AIS data and detailed records of lifting data (including shipper, origin and destination, quantity, ships). Both databases combined enable us to model the spatially disaggregated ship routing behavior at an appropriate scale. Previous research has been trying to provide descriptive analysis for ship traffic behaviors based on AIS data, such as traffic density and the average speed of a particular vessel type (Xiao, et al. 2015; Shelmerdine 2015). Analytical tools, specifically discrete choice models, traditionally used in transportation studies have not been used in the shipping sector to examine vessel behaviors. Furthermore, most research in the transportation field has focused on transport mode choice or port choice analysis (for example, Malchow and Kanafani 2001; Veldman, et al. 2011). The analysis of ships' destination choice behaviors appears to be an untapped area.

Our paper contributes to this topic by examining how a set of explanatory variables relating to market conditions influence a charterer's behavior regarding destination selection. Understanding the charterer's destination choice is vital in estimating traffic volume to a specific destination and in forecasting supply patterns. It can serve as an indicator of the potential traffic level in the destination ports. It is also critical information for shipowners' planning and vessel deployment decisions. Shipowners can better match their space and cargoes with the knowledge of the charterer's potential destinations. In such circumstances, the question of how a charterer chooses a destination is considered to be an important issue not only for charterers but also for energy transport as well as matching energy demand and supply.

The context of this study focuses on the liquefied petroleum gas (LPG) shipping market, particularly LPG cargoes lifted on very large gas carriers (VLGCs) from the US Gulf. Long-haul LPG volumes are predominantly lifted on VLGCs. Traditionally, the Middle East has been the main LPG export area, however, recent developments in oil markets in North America has illustrated how dynamic transformation opportunities could be in the US (Bai and Lam 2017). After the shale gas discovery, the US has become an increasingly important export regionfor LPG (Tan and Barton, 2017). LPG exports from the US increased significantly from around 9 million tonnes a year in 2013 to almost 24 million tonnes in 2016 (Waterborne LPG 2017). A substantial amount of USG originated LPG cargoes go to Asia and Europe.

This particular shipping segment is characterized by frequent trading activities due to arbitrage economics. On the demand side, there are three types of charterers: 1) downstream end-users, who normally sign long-term contracts with LPG producers to secure a fixed amount of volume for its own consumption. 2) oil majors, such as Shell and BP, who have upstream facilities to produce LPG. Oil majors can sell LPG on long-term contracts to fixed buyers, or trade them on spot markets based on current market conditions. 3) traders, who have no assets and purely profit from moving the cargo between different geographical locations. The major traders include Vitol, Trafigura, and Gunvor. Apart from the first type, the other two types of charterers can choose the destination based on market conditions. Although traders and oil majors may sign long-term contracts with the LPG producers in the Middle East and the US, however, the contract only specifies the volume and often does not specify the destination. For spot volume, destinations are normally not pre-determined for these cargoes at the time of fixing (normally two weeks before loading) and traders will decide whether to move the cargo to different locations based on market conditions at the time of loading.

On the supply side, based on Steem1960 market reports (Steem1960, 2018), the existing VLGC fleet as of April 2018 is 267 vessels, of which 204 are in the spot market. Thus, this paper deals with a shipping segment where nearly 80% of the fleet is in the spot market. Furthermore, for VLGC time charter contracts, although they are signed for a relatively long term, the contract still can be canceled or re-negotiated depending on trading economics (Payne and Aizhu

2016). Furthermore, the charterer or the disponent shipowner has the commercial control of the vessel under a time charter contract. Unless a ship on time charter is used exclusively for own cargo programme in a fixed trade, then, the destinations can still be altered on a time charter. As such, the contract type may not be that important. There are distinct differences between LPG and LNG shipping markets. The LNG shipping market is characterized by very long-term cargo contracts at fixed rates, with vessels built to satisfy specific contractual needs (Adland et al. 2008).

It is also acknowledged that in the natural resource shipping markets, such as crude oil, iron ore and coal markets, although many vessels operate in the spot market, a large proportion of trade volume is fixed under offtake agreements, thus the destination is normally not a ‘free choice’ (Babri et al., 2017). This is because sources and sinks are effectively fixed for natural resources. Countries with abundant resources will exploit and naturally become an export region. For import regions, they normally do not have sufficient resources. Furthermore, for products like crude oil, substitutes do not exist. Thus, demand regions have no choice but to import. This leads to sticky trade flows in this type of markets. However, for downstream products, like refined oil products, the supply and demand are not that fixed compared to natural resource markets. This is because on the one hand, substitutes can exist. For instance, LPG and naphtha can both be used as petrochemical feedstocks depending on the economics. On the other hand, for the same downstream product, take LPG as an example, the demand region can either choose to import directly or produce domestically using imported raw material crude oil. Hence, the trade flows in the downstream market are less sticky and destinations are changing dynamically based on market conditions and local refining capacity.

This section aims to propose a discrete choice model to predict charterers’ destination choice. A case study is presented in the VLGC destination choice analysis for cargoes originated from the US Gulf and identify its relationship with several explanatory attributes, including the freight rate, commodity price spread, bunker price and the number of ships in a specific area. The model could then be used to forecast the probability of VLGC vessels going to a specific direction, thus predicting future supply patterns in certain regions. The sample data is further divided into two sub-periods: Jan 2013 to May 2016 before the expansion of the Panama Canal and June 2016 to May 2017 after the canal expansion, which aims to identify the effects of the Panama Canal on decision making regarding destination choices. Furthermore, both aggregate and disaggregate analysis for different ports are provided. This model can be applied to other downstream commodity transport sectors where trade flows are not that sticky, arbitrage opportunities exist, and traders actively participate in the market, for example, the product tanker market for naphtha transport. Naphtha export from Europe to Asia arises mainly due to arbitrage economics.

4.3.1 Discrete choice analysis in transportation field

Discrete choice models have been widely used in freight transport studies, particularly in the field of mode choices, carrier selection, and port choice modeling. As noted, the selection of a transport mode, port and shipping carrier is a major logistics consideration for firms, as the costs incurred could significantly erode the value created (Magala and Sammons 2008). Baumol and Vinod (1970) for the first time developed a choice model to determine the optimal transport mode choice considering factors like freight rate, speed, en-route losses, and dependability. Nam (1997) discussed the market segmentation issues in freight transport choice modeling, specifically, he compared the aggregation and disaggregation approach over commodity groups by predicting powers.

In the maritime field, carrier selection and port choice have often been studied. Transport mode is most often compared between rail or truck, and less studied in the shipping domain. This is because in most cases, shipping transport is a must for global transportation and alternative modes are not available. Malchow and Kanafani (2004) modeled the selection of export ports as a function of geographic location, port specific characteristics and vessel schedules in the case of US ports. They identified the location of a port to be the most significant factor. Steven and Corsi (2012) further analyzed the attractiveness of ports for containerized shipments based on a series of factors including port characteristics, individual shipments, and actual freight charges by applying a discrete choice model.

Kashiha et al. (2016) studied the port choice decision made by shippers based on geography (whether coastal or landlocked countries) and transportation costs. On a different note, Rich et al. (2009) developed a freight demand model for the mode choice and crossing in the Oresund region. Piendl et al. (2016) studied the shipment size choice using a logit model to analyze interregional road freight transport. The model includes the transport mode of trucks, rails and ships, while the crossing choices cover either ferry routes or a bridge. Alizadeh et al. (2016) used a vessel based logit model to investigate the capacity retirement in the dry bulk market. Specifically, the authors studied the effect of vessel specifications such as age and size, as well as market variables, such as bunker price and the probability to scrap a dry bulk ship.

Destination choice modeling has not often been examined in freight transportation, but has been investigated in the pedestrian traveling domain. For instance, Timmermans (1996) employed the Multinomial Logit Model (MNL) to study the sequential mode and destination choice for shopping trips using travel survey data in Eindhoven, Netherlands. Pozsgay and Bhat (2001) studied the destination choice for home-based recreational trips using nonlinear-parameter MNL. Wang and Lo (2007) applied MNL to examine the supermarket destination choice utilizing stated shopping preference data of Chinese immigrants. Newman and Bernardin (2010) investigated the mode choice and destination choice for work tours by employing a hierarchical ordering nested logit model and concluded that hierarchical ordering of nested decision trees could be of advantage for location and mode choice modeling. Gonzalez et al. (2016) used a combined trip demand logit model to study the variables in the supply side that influence the bicycle sharing users' destination and route choices in Santiago, Chile.

In a short summary, most attention has been given to port choice or carrier selection analysis in the freight transportation field. Studies on the choice behavior of individual vessels are non-existent, let alone for destination choice analysis. This study aims to fill in the gap by studying the spatially disaggregated ship destination choice behaviors.

4.3.2 Methodology

This study uses a logit model, one of the most widely used methods in transport choice fields, to analyze the movements of commodities between the shipper's/carrier's origin and various destinations. The decision of which destination to go is modeled as a function of the characteristics describing market conditions such as freight rate, product price spread, bunker price, and the number of ships in one specific area.

This study takes both aggregate and disaggregate approaches for destination choice analysis. Specifically, the difference between different ports is accounted for in the model by comparing the utility functions between different ports. This is because different ports are operated by different terminal operators and some ports are controlled by specific entities, such as Freeport being the main export terminal for LPG producer Philips 66. Thus, these factors can also influence the destination choices. Furthermore, the expansion of the Panama Canal in June 2016 also brings significant changes. Before that, VLGCs from the US Gulf (USG) to Asia need to travel all the way via the Cape in Africa, while since then they could transit via the Panama Canal. The round-trip distance from Houston to Chiba, Japan has almost halved from 32,197 miles to 18,812 miles. Although the Panama Canal cost is estimated at $ 470,000 for a round voyage and nomination fee, the total freight cost per ton has been significantly reduced compared to transit via the Cape.

Normally the cargoes loaded in the US would have three main destinations, including Latin America/Caribbean, Europe/Mediterranean region (or West in general) and the Far East. However, LPG in Latin America is mainly used for household consumption and its price is often subsidized by the government to assist low-income families. Thus, it behaves less like a traded commodity. Social relevance and high weights in the consumer index make stable LPG price a policy priority. Domestic LPG price in Latin America countries has deviated from international LPG price fluctuations. There has been small but increases in domestic prices for the past decades to close a growing gap with the international price. It only stops whenever the international price drops. For example, the government of Brazil, which is a top LPG import country in Latin America, introduced an LPG subsidy program in 2002 to assist LPG purchases for low-income families through a gas voucher (IMF 2013). LPG import volume from Brazil has been steady over the past few years (1.91 million tons in 2014, 2.00 million tons in 2015 and 2.03 million tons in 2016) according to IHS Waterborne Report (2017). LPG consumers in Mexico have also enjoyed significant subsidies for almost a decade. The LPG price is fixed and adjusted monthly. As the sole producer and importer, Pemex remains absolute control over pricing policy before 2016. Total subsidies provided in Mexico amounted to 9.1 billion USD over 2003 to 2014. In El Salvador, the cost of LPG subsidies could account for around 0.6% of GDP in 2013 (IMF 2015). Considering above, imports into Latin America is more residential demand driven and less influenced by market fluctuations including international LPG price changes and freight cost volatility. Thus, this study only concentrates on the destination choice behavior of ships going West and East.

4.3.2.1 Model specification

Assume that a homogenous charterer, at time t, faces a choice among j possible destinations. The charterer would obtain a certain level of utility, in other words, profit from each alternative. Under the random utility framework, the charterer's utility from alternative j is $u_{tj} = v_{tj} + \varepsilon_{tj}$. v_{tj} is deterministic and is often referred to as representative utility, as it is known to the researcher using observable variable x_{tj}. The charterer at time t is supposed to choose the destination with the highest level of utility. However, as ε_{tj} is not observable and thus the charterer's choice is not deterministic and cannot be predicted with certainty. Therefore, a choice probability is derived. Different choice models are derived under different specifications of the density of unobserved factors (ε_{tj}), $f(\varepsilon_t)$. The logit model is by far the most widely used discrete choice model, which assumes that ε_{tj} is distributed iid extreme value for all j. The probability that a charterer at time t chooses destination j is

$$P_{tj} = \frac{e^{u_{tj}}}{\sum_{j=1}^{J} e^{u_{tj}}}$$

(4.1)

Where $j \in J$. J includes all possible destinations. Representative utility is usually specified to be a linear function of observable variables: $u_{tj} = \beta' x_{tj}$. Under this specification, the logit probabilities become:

$$P_{tj} = \frac{e^{\beta' x_{tj}}}{\sum_{j=1}^{J} e^{\beta' x_{tj}}}$$

(4.2)

4.3.2.2 The utility function

The main objective of this research is to test the effect of changes in market conditions on destination choices. Thus, at a given time t, for charterers, the main attributes to consider include product price spread, freight costs, bunker costs and the number of ships in a particular area. The monthly seasonality factor is not considered here, because there are no obvious seasonal differences for ships going to either the East or the West based on the sample data.

Based on the industrial knowledge, the following hypothesized relationships are proposed as follows:

Price spread: The essential profit for a trader/charterer to obtain is the arbitrage, which is the product price difference between the origin and destination minus total cost of transportation. The product price spread exists, as product prices are normally lower in producing countries and higher in consuming countries. A wider arbitrage window implies higher profit and could incentivize charterers to move more cargoes to the destination that yields higher returns. Thanks to the shale gas revolution, US LPG production cost has been reduced significantly and so does the domestic LPG price. US Propane Mt Belvieu Enterprise wet price is the benchmark price index for US domestic propane price, while propane prices in Europe and Asia are mostly reflected by European Propane CIF Amsterdam-

Rotterdam-Antwerp (ARA) (Argus) Large Cargoes and Propane Argus Far East Index (AFEI) respectively. Since 2013, the spreads between Propane ARA and Mt Belvieu price, and between AFEI and Mt Belvieu have been positive most of the time. The price spread is not constant but changes over time due to changing regional supply and demand dynamics. The price spread at the time of loading is used since traders look at the arbitrage window around the time of loading to decide the destination. Hence, Hypotheses 1 and 2 are set as:

H1 Higher spread.WEST will decrease the probability of ships going to the East.

H2 Higher spread.EAST will increase the probability of ships going to the East.

Freight rate (represented by Baltic LPG (BLPG) freight index). The main cost for charterers to move the cargo is the freight cost. The assessment of whether an arbitrage window is open is determined by the net spread (CIF price at destination – FOB price at source – freight rate). The BLPG freight index is often characterized by high volatility. For instance, BLPG dropped from 140 dollars per tonne in mid-2015 to around 20 dollars per tonne in mid-2016, which was an 85% decrease in one year. High volatility implies that freight costs vary dramatically at different times and could constitute an important attribute when charterers choose a specific destination since dollar per tonne costs typically are higher for long distance routes. When freight rates are high, the cost saving on freight could be larger for shorter voyages compared to low freight rate environment. In this study, the BLPG rate is used as a single indicator for freight movement to represent market dynamics. For the freight rate from USG, the rate is decided based on a base rate (BLPG equivalent) plus some premium. The calculation is based on the Baltic LPG index which tracks the freight from Ras Tanura in the Middle East to Chiba, Japan. The appropriate conversion to freight rate from USG is then made based on time charter equivalent (TCE) concept. Assume vessels should obtain a similar level of TCE wherever it sails from, the dollar per tonne rate from USG could be calculated backward based on TCE per day. There usually is a premium from the US over the Middle East on Baltic. For ships loading from the US to Europe, it is normally BLPG+5dollars and to Asia, it is BLPG+2 dollars. Thus, using BLPG rate can reflect the freight rate movement for both destinations at a specific time. It is also acknowledged that the implied regional rates based on such calculation may not be 100% accurate, since in the short run, freight markets are not fully integrated due to different regional supply and demand dynamics. However, since the Baltic index only has one LPG route available, the single BLPG rate is used as a proxy for freight rate movements. In the VLGC market, on average the cargo is loaded 2 weeks after the fixture occurs. So, in this study, we use the freight rate 2 weeks before the loading time to reflect the time lag. For the effect of the Panama Canal expansion, since the time difference between traveling to the East and the West has weakened, the hypothesis is the freight rate effect on destination choice post the Panama Canal expansion shall become weaker. We then set hypothesis 3 as:

H3 Higher freight rate will decrease the probability of ships going to the East before the expansion of the Panama Canal and such effect shall become weaker post the Canal expansion.

Bunker price: In reality, charterers need to pay for greater fuel cost to compensate shipowners, when they require the vessel to sail on longer routes. From the charterer's point of view, when the bunker price is high, the charterers will need to pay higher bunker costs if they choose to go to the East compared to the West due to longer distance. Regarding the Canal expansion effect, the shorter distance to Asia may make charterers indifferent to fuel costs when considering the destination. In the VLGC market, to hedge for bunker variability, the bunker cost is not decided when fixing the contract, while only the base freight rate is decided. The bunker cost is determined on the Bill of Lading date using Houston Platts bunker price for USG cargo. This study takes Houston IFO 380 bunker price as the attribute which reflects fuel cost development. As such, we have Hypothesis 4:

H4 Higher bunker price will decrease the probability of ships going to the East before the Panama Canal expansion, while after the expansion, such effect may be insignificant for charterers to consider.

The number of ships in a specific area may also be an important attribute to consider. Cargo movements to a particular destination could be ultimately attributed to the demand in that region. However, as demand could not be directly measured on a day-to-day basis, it could partially be reflected by the number of ships in that region. As more ships may imply current higher demand in the region. However, on the other hand, too many ships may imply oversupply and buyers may build up high inventory levels based on current supply, which the charterer needs to take into consideration. The number of ships in a particular region at time t is calculated based on AIS data. Polygons are drawn for each region. The East area includes coastal areas in the Far East and South-East Asia, while the West area includes Europe. AIS data provides information regarding a vessel's name, current position (both longitude and latitude) and speed, etc. By testing whether a particular VLGC is in the drawn polygon at time t and summing up all vessels staying in the polygon, we could obtain the total number of ships in a particular region at time t. In this paper, we count the total number of ships within each polygon irrespective of the ship's direction and loading condition, because Asia is pure import region for VLGCs and the number of VLGCs loading from North West Europe is rather limited (1 or 2 VLGCs per month). So, almost all VLGCs going to these regions can be considered as laden ships. Therefore, the next hypotheses are proposed as such:

H5 Higher number of ships in the East will increase the probability of ships going to the East.

H6 Higher number of ships in the West will decrease the probability of ships going to the East.

Thus, the utility function for charterers could be derived as:

$$\begin{aligned} u_{tj} = \beta_{1j}\mathrm{Spread.WEST}_t + \beta_{2j}\mathrm{Spread.EAST}_t + \beta_{3j}\mathrm{BLPG}_t \\ + \beta_{4j}\mathrm{Bunker\ Price}_t \\ + \beta_{5j}\mathrm{Ships.WEST}_t + \beta_{6j}\mathrm{Ships.EAST}_t \end{aligned} \tag{1}$$

where $\mathrm{Spread.WEST}_t$ is the price spread between Propane Mt Belvieu and ARA price at time t; $\mathrm{Spread.EAST}_t$ is the price spread between Propane Mt Belvieu and AFEI price at time t; $BLPG_t$ the Baltic LPG index, which measures the freight market condition at time t; $Bunker\ Price_t$ represents the Houston IFO380 bunker price. $Ships.WEST_t$ and $Ships.EAST_t$ represent the number of ships in the destination area West and East, respectively.

All variables included are individual specific variables which mean that they only vary across different time, but not across alternatives. It is noted that only the differences between these coefficients are relevant and may be identified. With two alternatives East (labeled 1) and West (labeled 0), the coefficients associated with West (0) is set to 0. The unit of measurement of u_{tj} is hypothetical, aslo refered to as utils. It can be thought of empirically as a measurement of "profit" (product price spread – cost of carry) obtained by moving the cargo.

4.3.3 Data and descriptive statistics

4.3.3.1 Data

For this study, data was gathered from various sources. Lifting data was obtained from Waterborne LPG lifting report (IHS, 2017). BLPG freight rate was collected from Baltic exchange. BLPG is the freight index for the VLGC market and measures the dollar per ton rate from Ras Tanura, Middle East to Chiba, Japan for a VLGC loading standard 44,000mt LPG. Price spread was retrieved from Argus. The description of the price spread data is described in Section 3. The number of ships in one specific area was calculated based on AIS data. The time period was from Jan 2013 to May 2017. A total of 692 samples (including East: 470 and West: 222) were included. The samples were further divided into two sub-periods: 1) Jan 2013 – May 2016, which was before the expansion of the Panama Canal. 405 samples were included, which consisted of 256 liftings going East and 149 liftings going West. 2) The second sub-period was from June 2016 to May 2017, which consisted of 287 samples (East: 214 and West 73). Liftings from different port origins were also grouped to compare the significance of various attributes across ports.

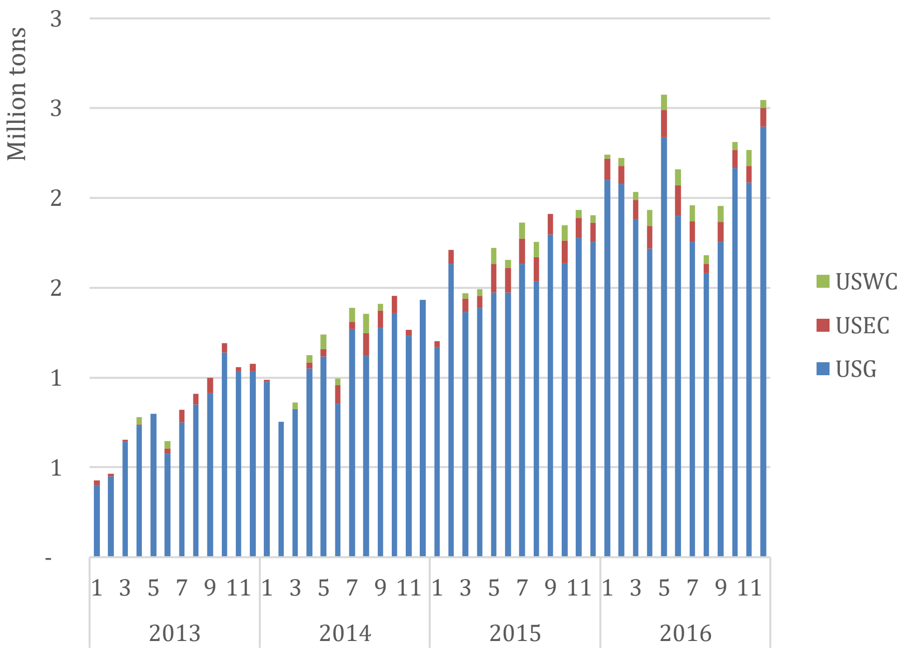
4.3.3.2 US LPG export statistics

US LPG export has increased substantially over the past few years. LPG could be loaded from the US Gulf Coast (USG), west coast (USWC) and east coast (USEC). Figure 4.12 indicates the geographical locations of major export ports. As can be seen, most export terminals are located in USG. Figure *4.13* and Table *4.12* show the monthly LPG export volume by exporting regions and annual export volume by loading ports respectively. USG remains the major export regions, while ports located in the east and west coasts export lesser volumes compared to USG. Exports from ports in USEC and USWC are mainly destined to Europe and the Far East respectively due to geographical proximity. However, destination choices for exports from USG seem more uncertain. This study thus mainly focuses on USG originated cargoes. Furthermore, as shown in Table *4.12*, among all USG ports, Houston, Galena Park and Nederland are the major export ports. Corpus Christi and Freeport in 2016 exported around 440,000mt cargoes each, which was considered a small quantity compared to the other three ports (IHS 2017). Thus, this study mainly investigates USG originated cargoes from Houston, Galena Park, and Nederland ports. Table 4.13 illustrates total US export to different destinations lifted on VLGCs. One trend to observe is the increasing proportion of volumes going to East over the past years, indicating greater demand from Asia.

Figure 4.12 US LPG port geographical location

Source: drawn by author.

Figure 4.13 US LPG export from major regions (Unit: million tons)



Source: drawn by author based on IHS (2017).

Table 4.12 Major US LPG port export statistics (Unit: tons)

Region	Port	Terminal operator	2016 export volume (tons)
USG	Houston, TX	Enterprise	12,283,379
	Galena Park, TX	Targa Resource	5,553,703
	Nederland, TX	Lone Star/Shell	4,875,371
	Corpus Christi, TX	Trafigura	489,848
	Freeport, TX	Phillips 66	433,000
USEC	Marcus Hook, PA	Sunoco	598,784
	Chesapeake, VA	DCP	85,220
USWC	Ferndale, WA	PetroGas (BP)	772,430

Source: compiled by author based on IHS (2017).

Table 4.13 Total US exports to different destinations since 2013 on VLGC (Unit: tons)

Year	East	Europe/MED/WAF	Latin America/Caribs	Total
2013	1,112,284 (15%)	1,524,821 (20%)	4,949,036(65%)	7,586,140
2014	2,690,034 (25%)	1,994,817(19%)	6,063,258 (56%)	10,748,109
2015	4,943,979 (33%)	2,364,496 (16%)	7,753,121(51%)	15,061,595
2016	10,127,620 (53%)	4,013,758(21%)	5,123,353 (27%)	19,264,731

Source: compiled by author based on IHS (2017).

4.3.3.3 Descriptive statistics

The statistics for USG and port specific data including BLPG, the number of ships in a specific area, spread.East and spread.West, as well as fuel oil price, are shown in Table 4.14 and Table 4.15. As can be seen, the proportion moving to East has increased from 63% before the expansion of the Panama Canal to 72% post-expansion, justifying splitting data into two sample periods. One important factor to note is the number of ships in a specific area. From the table, there seems to be an apparent difference between the average number of ships in the East for ships going East and West for the first sample period, while the number of ships in the West does not vary much for ships going East and West. This may imply that the more ships in the East, the larger chance to go to East in the first sample period. Last but not least, fuel oil appears to be an important factor to consider, as ships going West have higher average fuel oil prices than ships going East for the first sub-period. When the descriptive statistics for specific ports are compared, the proportion of ships moving to the East has all increased for three ports post the Panama Canal expansion, especially for the Galena Park, where the percentage has increased from 55% to 73%. At a first glance, when comparing the mean of descriptive statistics for different influencing factors, it varies across different ports and different sample periods, justifying the disaggregation approach for different ports.

Table 4.16 Descriptive statistics for USG data

USG Loading		Full sample period (Jan 2013 – May 2017)		Before Panama Canal expansion (Jan 2013 – May 2016)		Post Panama Canal expansion (Jun 2016 – May 2017)	
		East	West	East	West	East	West
BLPG	Mean (SD)	50.33 (31.60)	57.33 (33.02)	70.2 (31.32)	77.39 (27.42)	27.48 (4.35)	25.91 (4.32)
ships.WEST	Mean (SD)	10 (3.47)	9 (3.58)	7 (3)	7 (2)	12 (2.64)	12 (2.67)
ships.EAST	Mean (SD)	44 (8.93)	40 (9.34)	40 (8)	36 (7)	47 (7.43)	48 (7.33)
spread.WEST	Mean (SD)	99.98 (63.98)	117.94 (77.65)	116.39 (75.66)	150.77 (81.3)	74.93 (32.88)	68.4 (29.79)
spread.EAST	Mean (SD)	170.81 (91.88)	194.24 (104.24)	214.14 (97.37)	254 (87.53)	114.91 (45.17)	102.68 (41.38)
Fuel Oil	Mean (SD)	293.24 (127.31)	347.75 (161.09)	302.49 (167.22)	402.31 (185.2)	273.49 (31.9)	264.2 (32.2)
Sample size	# (%)	470 (68%)	222 (32%)	256 (63%)	149 (37%)	214 (75%)	73 (25%)

Standard deviations in parenthesis. # indicates the number of observations.

Source: Author.

Table 4.17 Descriptive statistics for port specific data

Loading Port		Houston		Galena Park		Nederland	
Before Panama Canal expansion (Jan 2013 – May 2016)							
		East	West	East	West	East	West
BLPG	Mean (SD)	68.45 (31.18)	72.49 (26.81)	74.66 (30.52)	89.93 (26.72)	71.72 (32.6)	75.53 (25.82)
ships.WEST	Mean (SD)	7 (3)	7 (3)	8 (2)	6 (2)	7 (3)	7 (3)
ships.EAST	Mean (SD)	40 (9)	36 (8)	38 (8)	32 (5)	43 (7)	41 (6)
spread.WEST	Mean (SD)	121.24 (83.87)	164.65 (95.18)	118.29 (69.77)	155.43 (55.18)	99.5 (46.6)	102.95 (36.34)
spread.EAST	Mean (SD)	217.32 (102.69)	260.73 (97.64)	223.31 (99.42)	277.84 (57.21)	196.09 (75.36)	202.31 (68.07)
Fuel Oil	Mean (SD)	323.43 (182.08)	420.47 (188.85)	310.2 (167.62)	489.3 (153.84)	230.01 (75.14)	232.88 (75.14)
Sample size	# (%)	160 (66%)	84 (34%)	45 (55%)	37 (45%)	51 (65%)	28 (35%)
Post Panama Canal expansion (Jun 2016 – May 2017)							
		East	West	East	West	East	West
BLPG	Mean (SD)	27.70 (4.32)	25.79 (4.39)	27.59 (4.46)	26.84 (4.11)	27.01 (4.38)	25.31 (4.48)
ships.WEST	Mean (SD)	12 (2.77)	12 (2.67)	12 (2.54)	13 (2.5)	12 (2.48)	11 (2.72)
ships.EAST	Mean (SD)	47 (7.53)	50 (6.52)	46 (7.48)	45 (8.65)	49 (7.16)	44 (6.44)
spread.WEST	Mean (SD)	78.04 (33.69)	69.63 (32.42)	70.75 (32.19)	71.86 (32.91)	72.27 (31.83)	62.26 (18.98)
spread.EAST	Mean (SD)	119.02 (45.08)	103.23 (47.64)	45.65 (99.03)	106.52 (36.04)	109.58 (45.04)	97.78 (30.24)
Fuel Oil	Mean (SD)	276.52 (31.73)	257.46 (33.20)	272.13 (29.31)	278.94 (27.96)	268.99 (33.82)	266.18 (30.19)
Sample size	# (%)	110 (73%)	40 (27%)	43 (73%)	16 (27%)	61 (78%)	17 (22%)

Standard deviations in parenthesis. # indicates the number of observations.

Source: Author.

4.3.4 Results, discussion and implication

Model estimation results for USG and port specific destination choice models from charterers' perspective are presented in Table 4.16. Based on the results, Hypotheses 4 and 5 are supported before the expansion of the Panama Canal, while Hypotheses 2 and 4 are supported post the expansion for USG as a whole. The significant attributes vary across different ports. In general, the Nederland port is worst depicted by the proposed attributes, where none of the variables is significant under two sample periods. The reason might be that the major charterers loading from the Nederland port are energy and chemical companies including Dow and Aygaz, who use LPG mainly as a downstream petrochemical feedstock. Thus, their demand is relatively stable, and the trading flows are stickier.

Before the expansion of the Panama Canal, for USG as a whole, bunker price and the number of ships in the East were significant determinants when choosing a destination. On the one hand, the more ships in the East, the larger the probability a ship goes to the East. Such hypothesis is also true for Houston and Galena Park ports. However, the average sensitivity to changes in the number of ships in the East varied across different ports. An increase of one ship in the East yields about a 3% increase ($e^{\beta_{\text{ships.EAST}}} - 1$) in odds to the East for the Houston and 5% increase in odds for the Galena Park. On the other hand, before the expansion of the Panama Canal, bunker price was a significant negative indicator for East destined ships for USG as a whole, as well as the Galena Park. The average sensitivity to changes in one dollar per tonne of bunker price leads to a 0.2% and 0.7% decrease in odds for choosing East destination for USG and the Galena Park respectively. Hypotheses 1&2 are supported for the Houston port, but not for the rest ports. The results are understandable. Based on our lifting database (data where charterers are identified), for the Houston port, before the expansion, the largest two charterers are Vitol and Trafigura, who account for 25% of the Houston port export volume. However, such proportion decreases to 16% post the expansion. Due to the shale gas revolution, LPG comes as a by-product and its price has dropped significantly since 2013. Traders are the first to take advantage of such price difference at that time. Their main consideration is the price arbitrage, whether they can profit more from moving to the East or to the West. Thus, the spread.West and spread.East are the main attributes to consider.

After the expansion of the Panama Canal, bunker price has become an insignificant attribute. This may be due to the fact that the distance and time required for traveling from USG to Asia have been reduced substantially and total bunker cost for charterers does not vary that much whether the vessel heads to the East or the West compared to previously via Cape to the East. However, lower bunker prices in 2016 may also be the reason that this factor has less impact on charterers' destination choice. The number of ships in the East, on the other hand, became a significant negative indicator for ships going East for the Houston port. This could be explained by the massive delivery of VLGCs since 2016 and the Canal expansion that allows more ships moving to the East, which ultimately caused oversupply and buyers' inventory build-up. The average number of ships in the East were 47 for East going ships and 48 for West post the Panama Canal expansion, compared to 40 and 36 before the expansion for the Houston port. Nevertheless, a large number of ships will also have an impact on price spread between the USG and the Far East, leading to less profits for traders.

In general, freight rate and the shipping capacity in the West are not significant attributes for all ports under both sample periods. For the freight rate, the result shows that it would not affect the destination choice at the time of loading since the rate is decided at the time of fixing and before loading. For the second factor, as regional LPG volumes are normally moved by smaller LPG carriers, the number of VLGC ships in the West region may not be an accurate proxy for the demand in that region.

Table 4.18 Results of vessel destination choice model

Variable	Coeff	USG	Houston	Galena Park	Nederland
Before Panama Canal expansion (Jan 2013 – May 2016)					
spread.WEST	β_1	-0.004 (0.004)	-0.012** (0.006)	0.003 (0.01)	0.000 (0.015)
spread.EAST	β_2	0.005 (0.004)	0.011** (0.005)	0.004 (0.009)	0.000 (0.010)
BLPG	β_3	-0.006 (0.005)	-0.011 (0.007)	-0.008 (0.013)	-0.008 (0.015)
Fuel.Oil	β_4	-0.002** (0.001)	-0.001 (0.001)	-0.007*** (0.002)	0.002 (0.005)
ships.WEST	β_5	0.018 (0.043)	-0.003 (0.057)	0.0035 (0.132)	0.011 (0.100)
ships.EAST	β_6	0.028*** (0.01)	0.029** (0.013)	0.053* (0.032)	0.016 (0.023)
Log-likelihood		-537	-294	-88	-101
R^2		0.208	0.220	0.356	0.132
Post Panama Canal expansion (Jun 2016 – May 2017)					
spread.WEST	β_1	-0.013 (0.012)	0.002 (0.019)	-0.058** (0.029)	0.014 (0.032)
spread.EAST	β_2	0.018** (0.009)	-0.003 (0.014)	0.044* (0.025)	0.007 (0.025)
BLPG	β_3	0.038 (0.035)	0.065 (0.054)	0.028 (0.108)	0.007 (0.0084)
Fuel.Oil	β_4	-0.005 (0.004)	0.014 (0.008)	-0.007 (0.014)	-0.018 (0.012)
ships.WEST	β_5	0.04 (0.051)	-0.08 (0.083)	0.001 (0.152)	0.165 (0.133)
ships.EAST	β_6	-0.001 (0.014)	-0.068*** (0.025)	0.037 (0.038)	0.045 (0.034)
Log-likelihood		-379	-151	-59	-74
R^2		0.328	0.383	0.382	0.445

***, ** and * indicate significance at 1%, 5% and 10%, respectively. Standard error in parenthesis. West destination serves as the reference level.

Source: Author.

In this study, the sample data is divided into two sub-periods: peri and post the Panama Canal expansion. The rationale is that ships going East have increased from 63% before the expansion to 72% post the expansion, indicating significant differences between the two periods. Furthermore, the expansion brings geographical changes (i.e. shorten the distance between the USG and the East), thus, the significant variables influencing ship spatial patterns may also be different. Initially, the logit model was built using the full sample data and incorporating a dummy variable to account for the Panama Canal expansion effect. However, the dummy variable was insignificant and failed to model the differences between the two periods.

This study provides implications for energy shipping, particularly for the industry to understand the charterers' rationale for choosing a destination. The significant attributes vary across different ports, as well as across different time frames, say, before and after the expansion of the Panama Canal. Overall speaking, charterers pay most attention to fuel cost and demand in the east before the expansion and the propane price spread post the expansion. Surprisingly, freight rate is considered insignificant. For charterers, since the freight rate is already decided at the time of fixing, it is shown to have no effect on their decision-making at the time of loading.

The significant attributes also vary across different ports, justifying panel comparisons between different ports. Different types of charterers loading from different ports and different terminal operators can be one of the main reasons. The Nederland seems to be less well described by the attributes, as all factors are insignificant. This might be due to the fact that the major charterers loading from this port are chemical companies, who move the cargo for its own downstream use. For ports where more traders are involved, factors such as product price spread and bunker price would play more significant roles. The overall low R^2 for the models can be due to the fact that certain VLGC cargoes are covered on a long-term contractual basis where destinations are predetermined, and less influenced by market variables.

The expansion of the Panama Canal brings significant changes to energy shipping, particularly for VLGCs, as they previously were too large to pass through Panama and needed to travel through Cape to reach Asia. It brings significant changes to both LPG trade flows and charterers' destination choices. On the one hand, it is observed that more volumes are heading to the East. After the expansion of the Panama Canal, time and distance have been reduced for VLGCs to reach Asia, so do bunker cost and freight cost. The net difference between going to the East and the West considering both propane price spread and regional freight rates becomes positive for most times post the expansion, as the freight rate to the East has lowered due to a shorter distance. Higher profits and demand attracts more cargoes to the East over the second period. On the other hand, the expansion of the Canal has made fuel cost a less concern for charterers to consider, while they focus more on the propane price spread post the expansion. It is noted that the maximum net difference between going to the East and the West is 100 dollars and 66% of the times the net difference falls within +/-60 dollars. Previously, although product price spread might be different for the East and the West, considering the higher bunker fuel compensation the charterer needs to pay to the East, the bunker price changes overweight the product price spread when charterers choose the destination. However, with the expansion of the Panama Canal, the bunker cost becomes irrelevant due to the shorter distance, and the product price spread now becomes a significant variable. Such phenomenon holds for both the USG as a whole and the Galena Park.

The number of ships in the East is a significant and interesting attribute to consider for charterers. It first was a positive indicator for ships going East. However, with more VLGCs delivered and heading to the East, it may cause oversupply and inventory build-up by buyers. Furthermore, it will have an impact on LPG prices in Asia and affect product price spread. It would result in less demand for LPG import and less profitable trading environments. Under such circumstances, this factor may become a deterrent for ships going East.

4.4 Conclusions

This chapter sheds lights on the understanding of the VLGC market. It has first analyzed the various relationships in the VLGC market between supply/demand, freight rate, newbuilding and secondhand vessel prices in an integrated framework. It then examines both the constant and time-varying dependency between VLGC freight rate and propane location price spread, crude oil prices, as well as between crude oil prices and propane prices in different locations by copula-GARCH model. In the last step, it proposes a discrete choice model for VLGC destination choice analysis for LPG cargoes originated from the US Gulf and identify its relationship with several explanatory attributes, including the freight rate, commodity price spread, bunker price and the number of ships in a specific area.

This study takes a novel perspective in investigating the freight rate formation, where freight rate is related to demand/supply and vessel prices in an integrated manner, thus any direct and indirect relationships could be identified. It also relates the freight rate development to the product spatial price spread, which has been valued by industrial practitioners, but never been studied in the maritime literature. Overall speaking, ton-mile demand plays the most significant role in affecting VLGC freight rates compared to other factors such as fleet size and product price spread.

This chapter has practical significance for shipping companies. This study aids shipowners' and charterers' decision making and forecasting process. By knowing the development of ton-mile demand, fleet size, crude oil prices and commodity product price spread, the industrial practitioners would have a clearer view of the shipping freight market movements. Furthermore, regarding destination choices, it is helpful for supply analysis and forecast in the destination region. The expected number of ships in a specific region could serve as an indicator for future port traffics. Such findings can be used by terminal operators to better plan their scheduling and operations. Furthermore, such results also provide insights for shipowners to better match their space with cargo, with the knowledge of the charter's potential destinations.

CHAPTER 5 DEPENDENCY AND EXTREME CO-MOVEMENTS ACROSS PRODUCT TANKER FREIGHT RATES

This chapter provides econometric analyses of the product tanker shipping market. Specifically, it examines dependencies and extreme co-movements across six major clean product tanker shipping freight rates by the copula-GARCH model. The findings provide significant implications for shipowners regarding decision making in many aspects, for example, portfolio diversifications and fleet deployment.

5.1 Background

The shipping sector is known to be disaggregated into different segments to carry different cargoes on specific routes. Thus, the freight rates of the different segments typically follow different movements largely driven by the supply and demand balances for different commodities transported (Kavussanos and Visvikis, 2006). However, on the other hand, substitution effects occur between vessels of adjacent size categories (Tsouknidis, 2016), as there are overlaps between cargo transportation in the same or adjacent routes. Substitutions between shipping segments occur when there is a significant difference in freight rates between the segments. Charterers may then choose to divide or combine cargoes, making it possible to take cargoes into another vessel segment. For example, for refined products from Middle East to Asia, if freight rate for LR1 tankers (60,000 – 79,999 dwt) is much lower than that for LR2 tankers (80,000 – 119,000 dwt), charterers previously using LR2 may choose to divide cargoes and load on LR1. Owners may also switch trading routes of their vessels for profit maximization purposes. A series of switches between sectors may take place until both markets return to equilibrium. Such substitutions make freight rates of the two vessel sizes or two trading routes interrelated with each other.

The trading routes of product shipping market are diverse across the globe. It is thus of interest to investigate the exact dependence structures and co-movements between freight rates of different trading routes and vessel sizes. Such findings would have significant implications for shipping participants, such as shipowners, regarding portfolio diversifications and asset allocations. Diversification in shipping is vital in view of a volatile shipping environment (Kavussanos, 2002, 2010; Lam and Wong, 2017). Diversification is accomplished when a shipowner does not invest only in one sector, but operates several types of vessels in different sectors. Diversification is also achieved by allocating vessels in different trading routes across the global network. Diversification could serve as a tool to overcome rivals, reduce risks or choose between options when highly uncertain about the market (Hitt et al., 1999). The benefit of diversification is to reduce the risk of loss in expected earnings. Kavussanos (2010) showed that diversification can be achieved by holding different size ships in bulk shipping, especially smaller size ships to reduce operational risks. However, on the other hand, Tsolakis (2005) argued that in the shipping domain, the high level of market integration makes diversification hard to achieve, especially in the dry bulk market. According to Tsolakis, risk reduction benefits may not be achieved by investing in more than one type of bulkers, but could be possible in more than one tanker type. Risk reduction benefits could be only obtained from the diversified fleet in certain cases (Koseoglu and Karagulle, 2013). Thus, it brings up the question of what is the level of market integration in the product tanker market and can diversification benefits be achieved in this market?

With regard to the dependence modeling, freight rates have demonstrated skewed and leptokurtic behaviors. As illustrated by Goulielmos & Psifia (2007), non-normality and non-linearity can be found in spot and time charter freight rate indices. Therefore, they conclude that linear and other traditional models are not suitable for modeling the distributions of the indices. Although t-distribution has been used previously to take into account fat tail behaviors that shipping freight rate exhibit both in the univariate case (Drobetz et al, 2010) and multivariate dimensions (Tsouknidis, 2016), the asymmetric correlation has not been well addressed in the literature. Like stock returns, shipping freight rates may exhibit asymmetric dependence and tail dependence structures, which are difficult to be captured by traditional multivariate time series model. Furthermore, as pointed by Jondeau and Rockinger (2006), for most kinds of univariate distributions it is not possible to extend to multivariate setup to capture the dependence structure. Freight rates may follow complex and dynamic marginal distributions, which makes it difficult to identify a multivariate extension based on their univariate distributions.

Cointegration test, VAR model, and multivariate GARCH models are the main techniques employed in the maritime literature to investigate freight relationships. Most of the methods are based on a linear framework, which fails to model the non-linear dependence structures between freight rates. Although multivariate GARCH models explored by recent researchers shed light on the exact dependence structure among the variables, these models may not be convenient to capture the asymmetric and tail dependence behaviors, which many return series may exhibit. Copula method overcomes such a problem by allowing flexible estimations of marginals with skewed Student-t distributions and different dependence structures separately. The model further allows tail dependences to be modeled in an accurate and easy manner.

In this study, we propose a copula-GARCH model for dependence modeling. Our copula-GARCH model nests a traditional GARCH model as a special case. The advantages of copula-based GARCH models over traditional multivariate GARCH models are that they can be applied to link together any type of marginal distributions that are proposed for the individual series. On the other hand, different dependence structures could link the same marginal distributions into different joint distributions (Lee and Long, 2009). Thus, different dependence structures could be compared and the best-fitted one could be selected. Furthermore, Copula method serves as a more flexible and accurate tool for dependence modeling. Asymmetric correlations and tail dependence could be easily estimated by copula functions.

The objective of this research is to examine the dependency structure between various product tanker shipping routes by copula-GARCH model. The copula-GARCH model is built on a two-stage method. Firstly, univariate ARMA-GARCH models are fitted separately to each freight rate series, with the assumption of independence between them. Then, the standardized residuals of ARMA-GARCH models are fitted in the copula function. This approach is of advantages as it provides the opportunity to model the margins (GARCH-based) and the associated dependency structures among different series (copula models) separately. To be more specific, GARCH models are employed first to capture the time-varying correlation of each series and then copula to identify the remaining dependence between standardized residuals, which are conditionally uncorrelated.

The contribution to the literature is threefold. Primarily, it serves as one of the few studies adopting the copula-GARCH model in the maritime field in order to capture the non-linear dependence and extreme co-movements across freight rates of different shipping routes. Copula model allows the marginal distributions to be estimated separately from joint distributions, thus provide more flexible and accurate dependence modeling. The model also captures the tail dependence, whether being symmetric or asymmetric, between different freight rates, which could be difficult to be estimated by traditional multivariate GARCH models. Secondly, the study sheds lights on the product tanker shipping market and its freight rate behavior, which has been a less researched area. Last but not least, it provides practical guidance for shipping practitioners. The knowledge of the degree of market integration in the product tanker market answers the question if diversification could be achieved. If diversification is possible, the dependence structures between freight rates on different trading routes would then aid shipowners regarding where to deploy their fleet to diversify and mitigate risks. Freight co-movements behavior under extreme market conditions will guide several participants in shipping, such as shipowners, charterers, and investors regarding hedging strategies and risk management.

The rest of the chapter is structured as follows: Section 5.2 describes the dataset and statistical properties, Section 5.3 provides results and discussions. The conclusion is provided in Section 5.4.

5.2 Data and descriptive statistics

The dataset contains daily freight rate for six different clean tanker shipping routes over the period from January 12, 2011, to Jan 12, 2016, a total of 1253 observations. The freight rate is measured in dollar per ton, which is calculated by taking the Worldscale (WS) rate published by Baltic Exchange multiplied by the flat rate and then divided by 100. The essential feature of WS is the flat rate where WS=100, which is reset at the beginning of each year by Worldscale Association. This represents a ton rate for a round trip between a given port pair by a standard vessel in standard conditions. Negotiated freight rates between shipowners and charterers are stated as a percentage of the nominal freight rate. The actual quotes are related to flat rate and reflect the state of the market and vessel size. WS quotes generally decline with increasing ship size as larger vessels have smaller unit costs when fully employed.

As the flat rate changes every year, WS rate is not comparable between different years. Therefore, it is necessary to convert it to a dollar per ton rate for historical comparison. Table 5.1 summarizes the freight index for key clean shipping routes and their respective descriptions. Four main size categories for product tankers are Handy size (25,000 – 34,999 dwt), Medium Range (MR) tankers (35,000 – 59,999 dwt), Long Range One (LR1) tankers (60,000 – 79,999 dwt) and Long Range Two (LR2) tankers (80,000 – 119,000 dwt). The TC1 rate represents long range two (LR2) tankers from the Middle East Gulf to Japan and TC5 rate represents the rate for the same route for long range one (LR1) vessels. TC2, TC11, and TC12 indicate freight index for MRs' major trading routes, while TC4 and TC6 represent major handysize trading routes. These freight rates are based on Worldscale (except for TC11, which is based on dollar per ton). To make freight rates across different years comparable, they are converted to US dollar per ton by appropriate conversion rates.

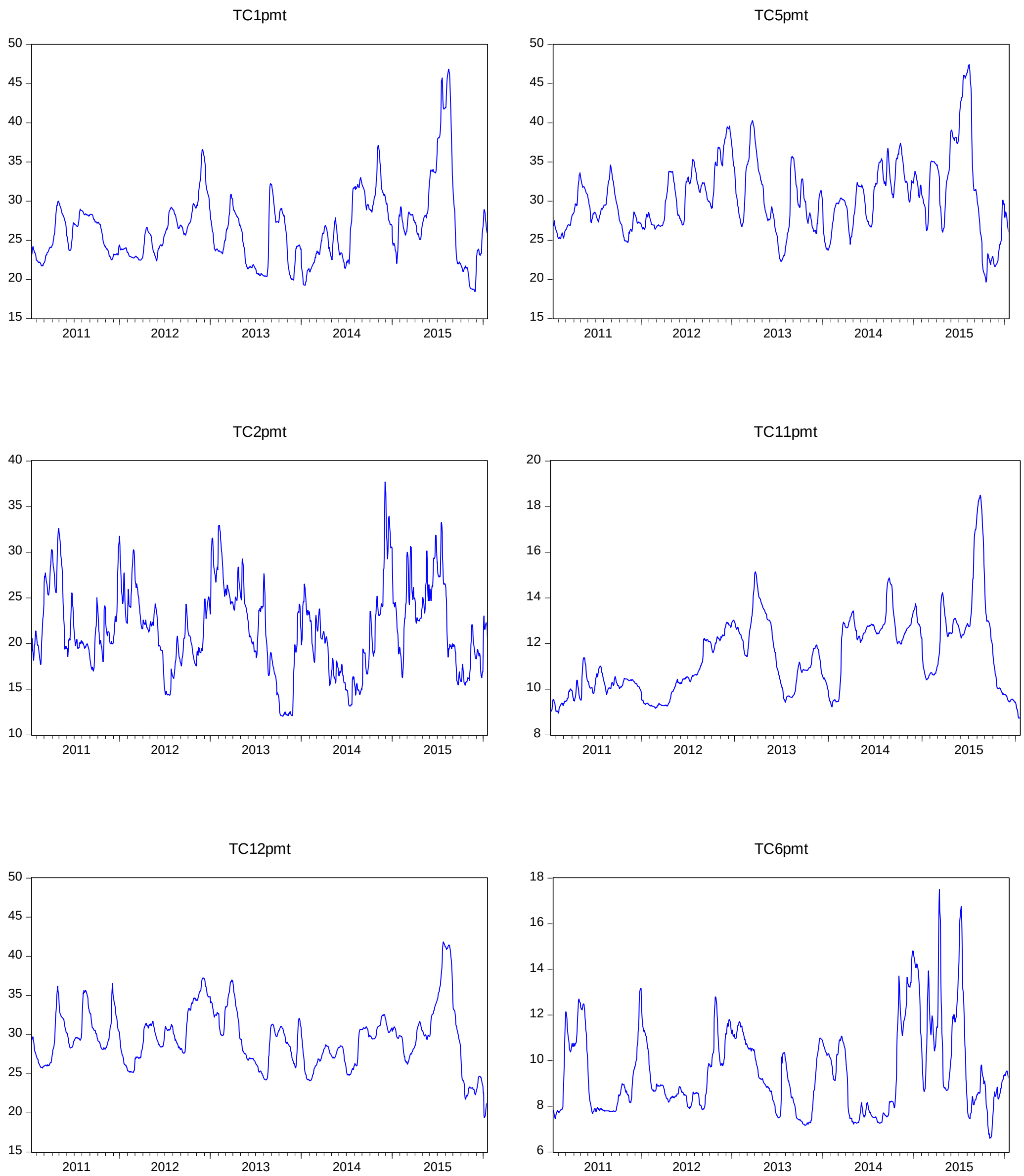
Table 5.1 Freight index for key clean product shipping routes and descriptions

Type	Index	Route	Loading port	Unloading port	Cargo type	Capacity (MT)	Data available since
LR2	TC1	Middle East Gulf to Japan (AG/JPN)	Ras Tanura	Yokohama	CPP, UNL, naphtha condensate	75000	Aug-98
LR1	TC5	Middle East Gulf to Japan (AG/JPN)	Ras Tanura	Yokohama	CPP, UNL, naphtha condensate	55000	Mar-03
MR	TC2	Continent to US Atlantic coast (UKC/USAC)	Rotterdam	New York	CPP, UNL	37000	Mar-04
	TC11	South Korea to Singapore	S. Korea	Singapore	CPP	40000	Apr-09
	TC12	West Coast India to Japan	Jamnagar	Chiba	naphtha condensate	40000	Jan-11
Handy	TC6	Algeria to European Mediterranean (WAF/MED)	Skikda	Lavera	CPP, UNL	30000	Jul-04

Source: compiled by author based on Baltic Exchange (2016).

Figure 5.1 shows the dollar per ton rate development for the six routes and their descriptive statistics are presented in Table 5.2.

Figure 5.1 Daily dollar per ton (pmt) rate for six clean shipping routes



Source: drawn by author based on Baltic Exchange (2016).

Table 5.2 Summary of descriptive statistics and stochastic properties of freight rates

	TC1PMT	TC2PMT	TC5PMT	TC6PMT	TC11PMT	TC12PMT
Mean	26.41790	21.62083	30.42767	9.503344	11.41518	29.53933
Max	46.87683	37.72088	47.45086	17.50544	18.50000	41.85120
Min	18.43111	12.03038	19.64655	6.599472	8.726000	19.37693
Std. Dev.	4.660395	4.711982	4.691013	1.887073	1.740974	3.734831
Skewness	1.431687	0.315378	0.790447	1.076863	1.017313	0.537331
Kurtosis	6.342963	2.831982	4.214712	4.048488	4.634471	3.784261
Jarque-Bera	1011.500	22.24506	207.5151	299.5644	355.6011	92.40698
ADF (lags)	-4.103901 (1)**	-5.131760 (1)**	-4.390876 (2)**	-5.624935 (3)**	-3.322355 (2)*	-3.678202**
PP	-3.769623**	-3.946390**	-3.989510**	-4.222345**	-3.038063*	-3.285391*
KPSS	0.356010	0.158258**	0.252135	0.184685	1.269423**	0.135772

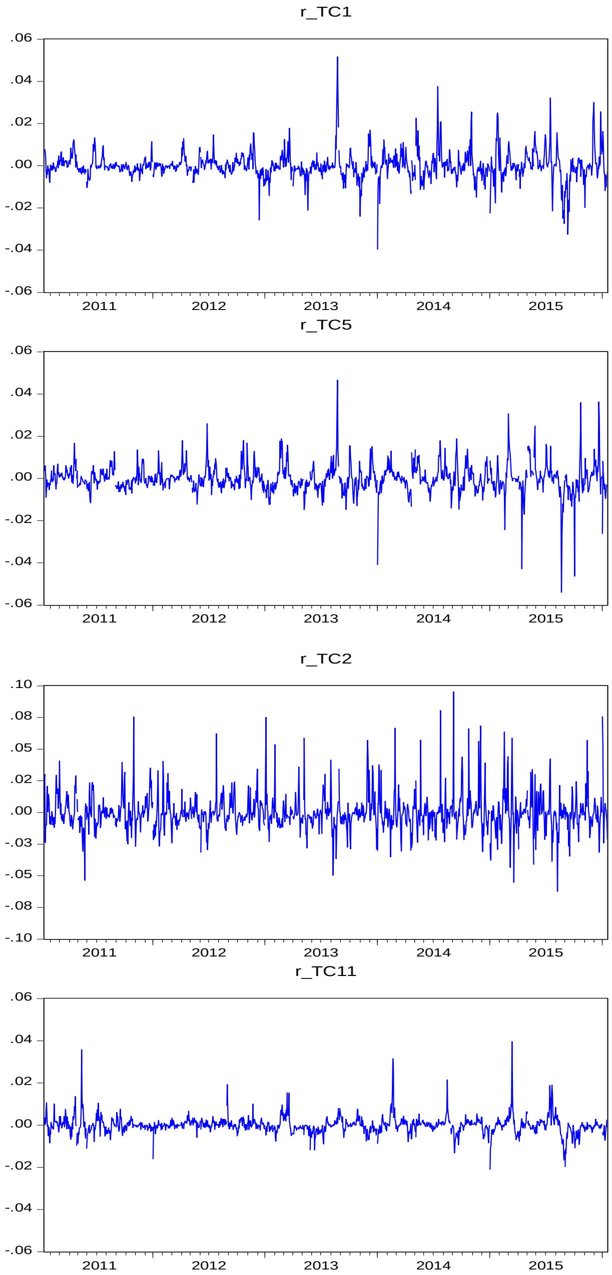
** Indicate significance at 1 per cent level, * indicate significance at 5 per cent level. ADF and PP test are unit root test against the null hypothesis of a unit root. KPSS is the stationarity test which has stationarity under null hypothesis.

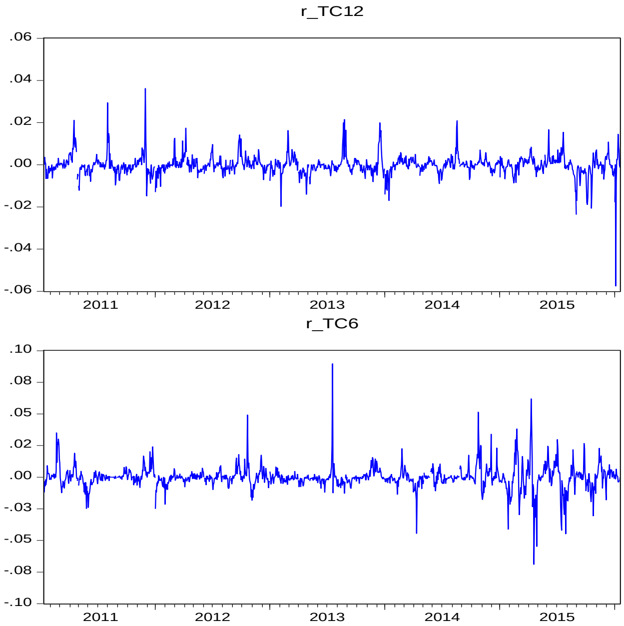
Source: Author.

ADF and PP tests have been criticized for their low power when the process is stationary but with a root close to the non-stationary boundary. The source of this problem is that, under the classical hypothesis-testing framework, the null hypothesis is never accepted. It is either rejected or not rejected. One method to overcome this is to perform stationarity tests where the null hypothesis assumes stationarity. The unit root test shows TC1, TC5, TC6, and TC12 are stationary in level form when converted to the dollar per ton from Worldscale. However, the test indicates inconsistent results for TC2 and TC11. Therefore, the stationarity cannot be concluded for these two freight rates in the level form.

To stabilize and centralize all the freight series, original data are transformed to log returns by calculating the difference in the logarithm of the two consecutive daily freight rates. Figure *5.2* shows the six return series. As observed from the graphs, volatilities of most routes tend to be higher from second half 2014 compared with the period of 2011 to 2013, this is the period when crude oil prices fall sharply, which changes refined oil trades dramatically and subsequently affects product shipping. TC2 returns are more volatile than other routes. This is because TC2 is the freight rate from the ARA region to New York, normally loading gasoline, and very much dependent on the gasoline price difference between the two regions. The volatile gasoline prices in the two regions increase the freight volatility. At an initial glance, there is volatility clustering effect, which means the tendency for volatility to appear in branches. It also shows evidence of non-constant conditional variance, as such, volatility may need to be modeled simultaneously in addition to modeling the mean series.

Figure 5.2 Daily Returns for six clean shipping routes





Source: Author.

The descriptive statistics of the return series are reported in Table 5.3. Returns are not normally distributed, instead, exhibit skewness and excess kurtosis behaviors. Jarque-Bera test confirms the non-normality. ADF, PP and KPSS tests all suggest stationarity of all return series. Ljung-Box (LB) *Q*-statistic was made to test autocorrelation and the results in Table 5.3 suggest that the null hypothesis of non-correlation are all rejected at 5 percent level and all series demonstrate autocorrelation. As such, an ARMA process would be appropriate. The presence of ARCH effects is confirmed by the results of Lagrange Multiplier tests for all return series. Therefore, the decision to use the GARCH models for marginal specifications is supported.

Table 5.3 Summary statistics and stochastic properties of return series

	R_TC1	R_TC2	R_TC5	R_TC6	R_TC11	R_TC12
Mean	0.000043	0.000047	-0.000007	0.000049	-0.000010	-0.000115
Max	0.051660	0.095299	0.046621	0.089724	0.039633	0.036176
Min	-0.039715	-0.062349	-0.054025	-0.068922	-0.021065	-0.057464
Std. Dev.	0.006596	0.014767	0.006718	0.009163	0.004191	0.004840
Skewness	0.855893	1.386625	-0.038409	0.769244	1.853942	-0.540393
Kurtosis	12.26335	9.489836	14.72250	19.70912	20.10456	25.20939
Jarque-Bera	4632.962	2600.439	7174.626	14699.87	15992.16	25813.11
ADF (lags)	-8.7488 (10)**	-10.99 (10)**	-8.998 (10)**	-10.172 (10)**	-9.1041 (10)**	-8.7869 (10)**
PP	-370.33**	-585.38**	-440.88**	-515.4**	-487.55**	-550.17**
KPSS	0.024336	0.020495	0.033829	0.018774	0.1538	0.078368
Q (5)	1382.4**	371.6**	1147.8**	1088.3**	1411.9**	1067.2**
Q (20)	1459.8**	413.5**	1253.1**	1248.1**	1533.6**	1178.4**
ARCH-LM (5)	11.32925**	6.92576**	6.26933**	42.55255**	14.77391**	14.77391**

** Indicate significance at 1 per cent level, * indicate significance at 5 per cent level. Q (5) and Q (20) are the Ljung-Box statistics for 5th and 20th order serial correlation. ARCH-LM refers to Engle's Lagrange Multiplier test for the presence of ARCH effects. ADF and PP test are unit root test against the null hypothesis of a unit root. KPSS is the stationarity test which has stationarity under null hypothesis.

Source: Author.

To get an initial idea of the correlation among all the return pairs, Table 5.4 shows the linear correlations, Kendall's tau and Spearman's rho rank correlations for all the return pairs. When the values are high and positive, it would suggest that two freight index move together in the same direction. The signs are mostly positive, indicating the most series move in the same directions in response to market conditions. However, the signs are negative for the pair TC2 and TC5, TC2 and TC12, TC6 and TC11 from all three dependence measures, indicating these pairs tend to move slightly in the opposite direction, although the relation is very low (all below 5 percent). TC1 and TC5 pair has the strongest linear dependence; the weakest dependences are between TC2 and TC11, TC6 and TC11. The three dependence measures are in line with each other, except for TC1-TC2 and TC1-TC6 pairs, where the linear correlation shows opposite signs compared to

Kendall and Spearman measures. The preliminary results suggest that the correlation for different vessel sizes operating on the same trade route is high, for example, TC1-TC5 pair. However, for the same vessel sizes, the correlation for different trading routes is low, especially for ships operating East of Suez and West of Suez, the correlation is lower than 5 percent, for example, TC2-TC11 and TC2-TC12 pairs. For the exact dependence measurement in the next stage, we only take the pairs with correlations over 10 percent for all measures.

Table 5.4 Linear correlation, Kendall’s tau and Spearman’s rho rank correlations for all the return pairs

	Linear Correlation	Kendall	Spearman
R_TC1-R_TC2	0.041	-0.020	-0.028
R_TC1-R_TC5	**0.429**	**0.330**	**0.468**
R_TC1-R_TC6	-0.022	0.007	0.010
R_TC1-R_TC11	**0.203**	**0.151**	**0.220**
R_TC1-R_TC12	**0.245**	**0.215**	**0.312**
R_TC2-R_TC5	-0.060	-0.033	-0.050
R_TC2-R_TC6	**0.177**	**0.134**	**0.196**
R_TC2-R_TC11	0.008	-0.014	-0.019
R_TC2-R_TC12	-0.039	-0.012	-0.017
R_TC5-R_TC6	0.033	0.031	0.046
R_TC5-R_TC11	**0.195**	**0.172**	**0.252**
R_TC5-R_TC12	**0.280**	**0.246**	**0.360**
R_TC6-R_TC11	-0.008	-0.012	-0.017
R_TC6-R_TC12	0.066	0.048	0.007
R_TC11-R_TC12	**0.291**	**0.196**	**0.283**

Source: Author.

5.3 Results and Discussion

This section presents the results of the marginal specifications and fitness of different copula models. Implications are also drawn based on the results.

5.3.1 Marginal specification results

Before applying copula functions to examine the dependence structure among different return series, the marginal should be correctively specified. Our analysis shows that all return series are correlated in terms of both the mean and variance. To better model these series, ARMA-GARCH models can be a good choice. The return series are then fitted to ARMA (p,q)-GARCH(1,1) process with skewed Student-t error distributions. The parameters p and q for each return series are estimated by different combinations from zero up to a maximum lag of five. The best-fitted models are then selected, determined by BIC Information Criterion. The best AR and MA lags are (1,0) for R_TC1, (1,0) for R_TC2, (1,1) for R_TC5, (1,1) for R_TC6, (1,1) for R_TC11 and (1,1) for R_TC12. Table 5.5 shows the parameter estimates for the marginal distributions. The p-values for Ljung-Box Q^2 statistics and ARCH-LM test for ARCH effect are not significant for all series, indicating the models could capture the autocorrelation and GARCH effects in a good manner.

Table 5.5 Marginal estimates with skewed Student-t distribution

	R_TC1	R_TC2	R_TC5	R_TC6	R_TC11	R_TC12
Mean equation						
μ	-0.000352	-0.000410	-0.000406	-0.000140	0.000045	-0.000272
	(0.000243)	(0.000545)	(0.000337)	(0.000594)	(0.000176)	(0.000201)
θ_1	0.631438**	0.462076**	0.720797**	0.705646**	0.773265**	0.703592**
	(0.021642)	(0.024459)	(0.024148)	(0.032830)	(0.022319)	(0.025896)
ϕ_1			-0.117198**	-0.206989**	-0.332568**	-0.203438**
			(0.038566)	(0.044377)	(0.035565)	(0.039903)
Variance equation						
ω	0.000003**	0.000052**	0.000009	0.000003	0.000002	0.000004**
	(0.000001)	(0.000018)	(0.000000)	(0.000003)	(0.000001)	(0.000000)
α	0.460986**	0.501714**	0.631673**	0.353824**	0.438609**	0.568122**
	(0.075806)	(0.124075)	(0.102773)	(0.056860)	(0.072683)	(0.078616)
β	0.538014**	0.497286**	0.347384**	0.645176**	0.560391**	0.430878**
	(0.028253)	(0.100730)	(0.049728)	(0.075138)	(0.036701)	(0.033292)
υ	2.841980**	2.488994**	2.621250**	2.877530**	2.639970**	2.562136**
	(0.137075)	(0.136720)	(0.082389)	(0.182176)	(0.096079)	(0.078737)
λ	1.020977**	1.125657**	1.061789**	1.035776**	1.044810**	0.984269**
	(0.035251)	(0.039663)	(0.037864)	(0.034929)	(0.036248)	(0.036412)
$Q^2(5)$ p-value	0.9673	0.7601	0.9429	0.7939	0.9393	0.7820
ARCH (5) p-value	0.9596	0.7451	0.8734	0.7882	0.9228	0.8308

**Represents significance at the 1 per cent level; * significance at 5 per cent level. Standard errors are in parenthesis.

Source: Author.

Different parameters have different economic meaning. α indicates the intensity of external shocks to volatilities and a higher value of α means more intense responses to market changes and a tendency to disperse further more. β, on the other hand, measures the memory of self-volatility. When $0 < \beta < 1$, the greater the value of β, the slower and longer the volatility decreases and lasts. The sum $(\alpha + \beta)$ measures the persistence of variance. When the sum approaches one, the persistence of shocks to volatility becomes greater.

The highest value of α is 0.6318 for TC5 and lowest is 0.3538 for TC6. The results indicate that the freight rate response of Middle East to Japan route for LR1 size (TC5) to outside shocks is more intense than the rest rates, while TC6 handysize route being relative irresponsive compared with the rest. On the one hand, the responsiveness to market shocks does not vary a lot across trading routes for the same vessel size. For example, TC2, TC11 and TC12 represent different routes for MRs and their α values are 0.5017, 0.4386 and 0.5681 respectively, indicating little variations. In fact, the responsiveness to market changes depends on the number of trading route options. The more options available, the more responsive the ships are. MR size ships are very flexible and can call almost all ports. However, for handysize vessels, they are small in size and limited to regional trades, thus the responsiveness tends to be low (α=0.3538). Besides, many of the handy vessels are chemical ships. The chemical market is normally less volatile than clean product market since it has a high COA coverage, especially in Europe. On the other hand, for different size vessels operating on the same route, the value of α varies a lot and tends to be higher for smaller vessels. For instance, TC1 and TC5, representing the Middle East to Japan freight for LR2 and LR1, the value of α are 0.4610 and 0.6317 respectively. The result is understandable as for vessels operating in the same route, LR1 vessels are more flexible and could switch routes more easily than the larger ones when the market condition changes, thus being more responsive. Furthermore, for LR2s, some of them are programmed or on contracts of affreightment (COAs), thus the corresponding responsiveness is compromised. The TC5 return has the lowest β value, suggesting that the shock to the volatility lasts for a shorter period than the rest routes. The results also show that for all return series, $(\alpha + \beta)$ almost approaches one, which indicates the shocks tend to persist.

5.3.2 Copula estimation results

With the conditional marginal models, we are now in a position to estimate copulas. We only report five different constant copula types here, as the rest copula types listed in Section 3.3.3 do not provide better fit compared to these five types. The estimated parameters for various copula functions are reported in Table 5.6. Out of the total 15 return pairs, only the pairs with correlation over 10 percent reported in Table 5.4 are estimated with copula models, as the relationships for the rest return pairs are too weak. The best-fitted copulas for each return pair are selected based on BIC criterion. Asymmetric tail dependences are found for 5 out of the 7 return pairs. The Clayton copula exhibits better explanatory ability than the other copula models for 4 return pairs, which indicates the dependence for the pair TC1-TC11, TC5-TC11, TC5-TC12 and TC11-TC12 tends to be higher in market downturns. For the pair TC2-TC6, Gumbel copula is selected. The result indicates that TC2-TC6 pairs tend to have upper tail dependence, which means the correlation is high in market upturns. For example, an increase in TC6 handy rates will quickly attract MR ships previously doing TC2 routes to take part cargoes ex-Mediterranean, thus reducing the supply of ships engaging in TC2 trade, which drives up the TC2 rates. Shipowners are profit driven, thus it gives more incentives to switch routes when the rate on a specific route is rising and become more profitable compared to alternative routes. However, in a market downturn, owners are less motived to change, as they have in general fewer options and potentially high opportunity cost. Thus, the dependence is higher in the upper right tail. For the rest two pairs (TC1-TC5 pair and TC1-TC12 pair), introducing the asymmetric tail dependence does not add many explanatory abilities. Furthermore, in almost all cases Gaussian copula underperforms the rest copulas (except TC1-TC12), suggesting rejection of no tail dependence. Another observation is that the relationship of trade lanes in the West of Suez and East of Suez is often very low, as such not reported in Table 5.6. TC2 and TC6 are the trade routes West of Suez, while TC1, TC5, TC11, and TC12 are east of Suez routes. TC2 is only paired with TC6 for copula estimations, not with any routes in the east due to the low correlation, and the same for TC6. The results indicate that product shipping market is geographically segmented, particularly East of Suez and West of Suez, where the correlation is extremely low.

Table 5.6 Estimates for the copula models

	TC1-TC5	TC1- TC11	TC1- TC12	TC2-TC6	TC5-TC11	TC5-TC12	TC11-TC12
Gaussian							
ρ	0.20405**	0.04292	0.13469**	0.11173**	0.07475**	0.10643**	0.17927**
	(0.02676)	(0.02845)	(0.02775)	(0.02799)	(0.02829)	(0.02804)	(0.02716)
LL	26.15	1.13	11.25	7.72	3.44	7.00	20.08
BIC	-45.17	4.87	**-15.37**	-8.30	0.25	-6.86	-33.02
Student-t							
ρ	0.20373**	0.04091	0.13357**	0.11295**	0.07171*	0.10489**	0.17431**
	(0.02868)	(0.02915)	(0.02869)	(0.02928)	(0.02973)	(0.02936)	(0.02914)
v	11.81459*	40.83705	27.31881	17.89887	17.29162	18.04100	12.75162*
	(4.71508)	(50.26458)	(22.91371)	(10.63807)	(9.69059)	(10.27965)	(5.56929)
LL	29.91	1.48	12.02	9.02	5.23	8.76	23.04
BIC	**-45.55**	11.31	-9.78	-3.77	3.81	-3.24	-31.82
Clayton							
θ	0.22820**	0.08477**	0.14671**	0.07818*	0.11308**	0.11564**	0.22895**
	(0.03906)	(0.03171)	(0.03587)	(0.03469)	(0.03364)	(0.03427)	(0.03795)
LL	22.08	4.33	10.46	2.88	7.00	7.09	24.09
BIC	-37.03	**-1.53**	-13.78	1.38	**-6.86**	**-7.04**	**-41.05**
Gumbel							
θ	1.13385**	1.00246**	1.06909**	1.07997**	1.02655**	1.06157**	1.10110**
	(0.02246)	(0.01771)	(0.02021)	(0.01969)	(0.01865)	(0.01941)	(0.02143)
LL	24.44	0.01	7.11	11.46	1.10	6.36	14.60
BIC	-41.75	7.11	-7.09	**-15.79**	4.94	-5.59	-22.07
Frank							
θ	1.1896**	0.1918	0.7595**	0.6685**	0.3594*	0.5873**	0.9856**
	(0.1735)	(0.1704)	(0.1707)	(0.1725)	(0.1708)	(0.1707)	(0.1730)
LL	23.49	0.63	9.90	7.51	2.21	5.92	16.20
BIC	-39.85	5.87	-12.66	-7.88	2.71	-4.71	-25.27

Based on equations (3.7) to (3.11). Standard errors are in parenthesis. log-likelihood and BIC value for different specifications for each pair are reported. The minimum BIC value is in bold, implying the best fitting copula for each return pairs. ** indicates significance at 1 percent level and * indicates significance at 5 percent level. LL stands for Log-Likelihood.

Source: Author.

Table 5.7 presents the values of Kendall's τ, the lower and the upper tail dependence coefficients, estimated from the copula with the best fit. Kendall's τ values suggest TC1-TC5 has the highest dependence, followed by TC11-TC12 return pairs, while tail dependence coefficients indicate that all the pairs show some degree of extreme co-movements, except for TC1 and TC12. TC2 and TC6 have the highest extreme co-movements in a bull market as the upper tail coefficient is 0.1001. The second strongest extreme co-movement is found for TC11-TC12, which is higher in a market downturn. For the TC1-TC5 pair, it is symmetric in both bear and bull markets as indicated by the same lower and upper tail dependence coefficients (0.0484). Although TC1-TC11, TC5-TC11, and TC5-TC12 pairs have lower tail dependences, their extreme co-movements in a market downturn is limited, as the pairs only have slight lower tail dependences with coefficients almost approaching zero.

Table 5.7 Kendall's τ and tail dependence coefficients of best-fitted copula

Return pairs	Kendall's τ	λ_L	λ_U
TC1-TC5	0.1306	0.0123	0.0123
TC1-TC11	0.0407	0.0003	0
TC1- TC12	0.0860	0	0
TC2-TC6	0.0740	0	0.1001
TC5-TC11	0.0535	0.0022	0
TC5-TC12	0.0547	0.0025	0
TC11-TC12	0.1027	0.0484	0

Source: Author.

5.3.3 Implications

The results have significant implications for both the academic field and industry practitioners. We have for the first time explored the exact dependence structure between different freight rates, allowing them to be skewed Student-t distributed. This has abandoned the standard normality assumption and better depicted the excess kurtosis and skewness of freight characteristics. The study also makes original contributions to the investigation of tail dependences among freight rates. The findings would provide useful guidance for shipping players. It is vital for them to understand the dependencies between different trade routes for diversification purposes and risk mitigations. The findings indicate that product tanker shipping market is quite fragmented and separated by geographical locations. On the one hand, the correlation is high for ships with different sizes operating in the same trade route. For example, TC1 and TC5, which represents the Middle East to Japan trading routes for LR2 and LR1, has the highest dependency among all the pairs. On the other hand, the freight rates of same size ships operating in adjacent regions have higher dependencies compared with the ships operating in distant areas, say East and West. For example, TC2, TC11, and TC12 all represent trading routes for MR size vessels. TC2 is the route from Continent to US Atlantic Coast, which is West of Suez, while TC11 and TC12 are East of Suez routes, namely South Korea to Singapore and West Coast India to Japan, respectively. The dependency between TC11 and TC12 is much higher than the dependency between TC2-TC11 and TC2-TC12 pairs. Furthermore, the dependencies for different size vessels operating in adjacent trade routes could also be high, for instance, the dependency between TC1-TC12, TC5-TC12 as well as TC2-TC6. Such a relationship exists due to the substitution effects of different vessel size categories. For example, when there is an increase in demand and subsequently freight rates for the Middle East to Japan routes, MRs previously loading West Coast India will take cargoes ex-Middle East if it is found to be profitable. The geographical approximation will allow ships to switch routes quickly and incur fewer opportunity costs, thus resulting in higher dependency structures between adjacent trading routes.

It is also noted that the geographical segmentation is largely attributed to the fact that freight rate changes depend highly on regional product flows. The price spread, regional product balances are the key determinants for freight rate. The freight rates of the other trade routes do play a role in affecting freight rate on a certain route, however, the spill-over effects are only limited to the same or adjacent routes. This implies that for shipowners, it is wiser to deploy the vessels in different locations, both East of Suez and West Suez for diversification purposes. Allocating different size ships in the same trade route could barely mitigate risks. In addition, the examination of tail dependence structures and the implied extreme co-movements between different pairs also has practical significance. Out of the 7 trade route pairs estimated by copula models, 6 have tail dependences and 4 have lower tail dependences, which means that they tend to co-move in market downturns. However, the lower tail dependence coefficients are close to zero for TC1-TC11, TC5-TC11, and TC5-TC12 return pairs. Normal copula is selected for TC1-TC12, indicating no tail dependence. As such, there seem to be no obvious extreme co-movements between the Middle East to Japan routes and West Coast India to Japan, South Korea to Singapore routes. Student-t copula is selected for the TC1-TC5 pair, indicating the symmetric dependency under extreme market conditions. For TC2-TC6 pair, Gumbel copula performs better than the other types and thus indicates the extreme co-movements in a market upturn.

5.4 Conclusions

This chapter investigates the dependency and extreme co-movements between different product tanker routes using copula-GARCH approach. The marginal and dependence structure are estimated separately in two stages, allowing for more flexibility and accuracy. Firstly we model the marginal as an ARMA (p,q)-GARCH(1,1) process with skewed-t distributions. The best fitted (p,q) legs are selected based on the BIC criterion. Then different types of copulas are fitted to the standardized residuals obtained from the marginal specifications and the best-fitted copulas are chosen by information criteria. The results show that Clayton copula provides the best fit for 4 out of 7 freight pairs. In addition, Gaussian copula underperforms other types of copulas in most cases, indicating significant tail dependence between different series. The findings suggest that product tanker shipping market is regionalized and segmented by geographical locations, especially West of Suez and East of Suez. As a new finding, the dependency for different size ships operating in the same trade route is high. Besides, freight rates of same size ships operating in adjacent regions have higher dependencies compared with the ships operating in distant areas. The dependency between the West of Suez and the East of Suez routes is quite weak. Furthermore, the findings suggest TC1-TC5 tends to co-move symmetrically in both bull and bear markets, whereas the extreme co-movements tend to be high for TC2-TC6 under market upturns and TC11-TC12 in market downturns. Therefore, for risk-averse investors, investing in different vessel sizes but employing them on the same trade route would not mitigate risks. Diversification can be achieved by deploying in different distant trading routes. Nevertheless, the results provide practical guidance for shipowners regarding risk mitigation and diversification, but not profit maximization based on daily return movements. To maximize profit, shipowners care more about $/day earnings on different routes, instead of relative rate return movements.

CHAPTER 6 CONCLUSION AND RECOMMENDATIONS FOR FUTURE RESEARCH

This chapter serves as the last chapter of this thesis. All the research objectives set out in Chapter 1 were achieved through conducting research process in Chapter 2 through Chapter 5 sequentially. The main findings and contributions achieved in this thesis are summarized in this chapter. It also points out research limitations and recommendations for future research.

Through conducting an in-depth literature review in the domain of econometric analysis in bulk shipping freight market, it is found that few research attentions have been given to the LPG and product tanker shipping markets. Furthermore, studies relating different market variables in an integrated manner are relatively scarce. In addition, research on the freight dependencies is most often based on linear models, which fails to capture the non-linear and time-varying dependency structure in a multivariate manner. Last but not least, research on vessels' spatial behaviors and destination choices from an econometric point of view is rather limited. The above-mentioned research gaps were identified through a systematic literature review in Chapter 2. Chapter 4 and 5 fulfilled specific research gaps. Chapter 4 provides econometric analyses of the LPG shipping market, particularly VLGC market. It takes a novel perspective in investigating the freight formation process, relating it to supply/demand factors, newbuilding/secondhand shipping market, as well as product price location price spread. It further examines vessels' destination choice behavior and identifies its associations with various market variables. It was considered as one of the first destination choice analysis in the maritime domain. Chapter 5 takes a disaggregate approach in studying the product tanker market. It assesses the dependency structure and extreme co-movements across major clean product tanker routes, which has significant implication for diversification and owners' portfolio management. Such research can be used for shipping practitioners, like shipowners and charterers while making investment, chartering and fleet deployment decisions.

6.1 Summary of major findings

The research objectives are stated in Chapter 1 and achieved in the following chapters. This section summarizes the major findings with regard to each objective accomplishment.

1) *To examine the relationships between the key market variables (supply/demand, freight rates, and secondhand and newbuilding prices) in the VLGC market in an integrated approach;*

This objective has been achieved in Section 4.1 using Structural Equation modeling approach. There are several important findings. Firstly, the study has identified the uniqueness and volatility of ton-mile demand changes in the VLGC market and its significant impact on freight rate determination. To have a clear understanding of freight rate movements, shipping practitioners should not look at fleet supply alone, but they should also pay attention to ton-mile demand forecasts. Secondly, the freight rate is identified as the dominant factor for secondhand vessel prices. The influence of freight rates on newbuilding prices is rather indirect, with secondhand vessel prices acting as a mediator. Furthermore, the impact of supply and demand on vessel prices, both newbuilding and secondhand, are found to be rather indirect.

2) *To investigate the dependency between VLGC freight rates and product price spread and oil prices;*

Section 4.2 has met this objective. It examines both the constant and time-varying conditional dependency between BLPG freight rate and propane location price spread, crude oil prices, as well as between crude oil price and propane prices in different locations by conditional copula-GARCH model. The results show that firstly, the dependency between BLPG freight rate and AFEI-CP swap spread, being the price spread between propane Far East and Middle East price, could be best described by a time-varying Rotated Gumbel GAS copula, indicating the higher dependence in the market downturns. Furthermore, BLPG and AFEI-US spread, being the spread between Far East and US prices, also have time-varying dependence and the relationship has strengthened since 2013 when the US gradually becomes a huge LPG exporter due to shale gas revolution. In fact, the relationship is relatively weak both in absolute terms and compared to that between BLPG and AFEI-CP swap. However, with more US volume exported, such a relationship is expected to continue increasing. The results further contribute to the understanding of how the oil price affects VLGC freight rate and the location price spread. Middle East propane price is found to have the strongest correlation with crude oil price compared to Far East and US prices, indicating higher sensitivity to crude oil price changes. In addition, the overall dependency between crude oil and BLPG freight rate is positive, although crude oil has a negative relationship with the arbitrage economics in a low oil price environment. This indicates the different and dynamic roles crude oil play in affecting the freight rate, both in terms of arbitrage economics and shipping demand.

3) *To study the spatial patterns of the VLGC market and examining how a set of explanatory variables relating to market conditions influence a charterer's behavior regarding destination choices.*

This objective has been attained in Section 4.3 using logistic regression for destination choice analysis. Attributes include freight rate, propane price spread, bunker costs and the number of ships in the destination areas. The results show that the type of charterers has a significant impact on whether the destination can be 'free choice'. Traders and oil majors tend to move the cargo based on arbitrage economics, fuel cost and demand in the destination region, while downstream consumers tend to be less influenced by market conditions and normally have fixed volume and trading patterns. The expansion of the Panama Canal brings significant changes to charterers with regards to destination choice. With time and distance reduction, bunker prices become insignificant for charterers' destination decision making, on the other hand, product price difference becomes significant to consider.

4) *To examine the dependency structure and extreme co-movements across various product tanker routes;*

Chapter 5 has achieved this objective by using a Copula-GARCH model. The findings suggest that product tanker shipping market is regionalized and segmented by geographical locations, especially West of Suez and East of Suez. As a new finding, the dependency for different size ships operating in the same trade route is high. Besides, freight rates of same size ships operating in adjacent regions have higher dependencies compared with the ships operating in distant areas. The dependency between West of Suez and East of Suez routes is quite weak. Furthermore, the findings suggest TC1-TC5 tends to co-move symmetrically in both bull and bear markets, whereas the extreme co-movements tend to be high for TC2-TC6 under market upturns and TC11-TC12 in market downturns. Therefore, for risk-averse investors, investing in different vessel sizes but employing them on the same trade route would not mitigate risks. Diversification can be achieved by deploying in different distant trading routes.

6.2 Research contributions

By achieving the above-mentioned objectives, this thesis has made several contributions, which are summarized below.

1) Chapter 2 contributes to the overall understanding of bulk shipping literature. It identifies the major themes and methodologies. It summarizes the general research trend and potential future research areas. Future research could include the application of methods developed in the financial field to the maritime domain, as well as combine AIS data with econometric techniques for shipping market analysis. It can be used as a reference for future research directions.
2) The contributions of Chapter 4 are multi-faceted. Overall speaking, it contributes to the understanding of the LPG shipping market, particularly, the VLGC market.

   Specifically, Section 4.1 has practical contributions: the results of this study could help shipowners and related companies to understand changes in ton-mile demand and fleet size, and their effect on freight rates and ship prices. This, in turn, could aid decision makers in chartering and investment decisions.

Section 4.2 contributes to the existing literature in the following ways. Firstly, this study takes a novel perspective in investigating the freight rate formation, relating the freight rate development to the product spatial price spread, which has not been studied in the literature. Secondly, it contributes to the understanding of how the oil price affects VLGC freight rate and the product price spread. Thirdly, this research makes methodological advancements by introducing the conditional copula-GARCH model with both constant and time-varying dependence parameters into the field of energy transport economics. Freight rate, crude oil, and propane prices have been found to be skewed and leptokurtic and may have completely different marginal distributions. They may also exhibit asymmetric, tail dependence or even time-varying dependency structure. This makes the traditional multivariate GARCH model inaccurate in addressing such relationships. This research has adopted the copula-GARCH method to overcome the drawbacks of multivariate GARCH models and provide a more flexible and accurate estimation for the dependency structure. Last but not least, this study also has practical significance for LPG transport and trade. This study aids shipowners' and charterers' decision making and forecasting process. By knowing the development of crude oil price and the product price spread, industry practitioners have a clearer view of the shipping market movements.

The contributions of Section 4.3 are twofold. Firstly, this work has made implications for energy shipping, especially for the gas sector. It is helpful for supply analysis and forecast in the destination region. The expected number of ships in a specific region could serve as an indicator for future port traffics. Such findings can be used by terminal operators to better plan their scheduling and operations. Furthermore, such results also provide insights for shipowners to better match their space with cargo, with the knowledge of the charter's potential destinations. This model can also be applied to other downstream commodity transport sectors where trade flows are not that sticky, arbitrage opportunities exist, and traders actively participate in the market. Secondly, this model advances the understanding of VLGC market spatial patterns and the application of AIS data in the field of energy transport. Previously, AIS data has been mostly used for descriptive analysis through visual inspection of shipping activities, or for safety concerns.

Chapter 5 has made original contributions to the understanding of exact dependence structure and tail dependencies across different trading routes, which cannot be captured easily by conventional multivariate GARCH models. The methodological advancements are twofold. In the first place, this chapter examines the tail dependency structure between freight rates, which has seldom been addressed in previous literature. This has significant implications for risk management. For example, the existence of lower (upper) tail dependence would imply a much higher downside (upside) risk in the product tanker shipping market, compared to the no-tail dependence scenario. Secondly, the freight rate return is allowed to be skewed-t distributed to better depict the skewness and excess kurtosis found in freight returns. Last but not least, this study also fills in the literature gap and contributes to the understanding of product tanker shipping markets with implications for portfolio diversifications, risk management, and fleet deployment purposes. Results have shown that product tanker shipping market is rather fragmented and segmented by geographical locations. Thus, the diversification benefits could be obtained by deploying vessels in distant trading routes.

In a summary, this thesis contributes to the understanding of LPG and product tanker shipping market using econometric techniques. From a theoretical perspective, it introduces new econometric models, previously applied in other fields into the maritime domain to tackle the previously unsolved problems. For example, structural equation modeling, copula models, and discrete choice analysis are used. From a practical perspective, this research provides useful information for shipping practitioners (shipowners, charterers, and investors) regarding decision makings in many aspects, for example, ship investment, chartering, fleet deployment and budget planning, to name just a few.

6.3 Research limitations and future work

The limitations of the current research and possible future research areas to improve this study are identified and presented in the following.

Firstly, one limitation of this study is that it considers only physical freight rates which include spot and period rates in the bulk shipping market. The forward freight agreement (FFA) market alone is not included as it is often viewed as a financial risk management instrument and used to hedge huge physical freight fluctuations. Future researches can further explore this separate field.

For Chapter 4, Section 4.1 tests the contemporaneous relationship between market variables. However, as noted by Adland and Jia (2015), newbuilding price and secondhand vessel price may not be directly comparable due to time-varying delivery lag. Future research can build upon the model by considering this time difference, which requires more detailed newbuilding contract and delivery data. Additionally, this study considers specifically the interrelationship within the VLGC market and does not account for the spillover effect between this market and smaller segments. Future research can push forward by incorporating interaction effects with other markets. Further studies could conduct multiple-group modeling in the different LPG sub-sectors, especially in the area of measurement invariance, to investigate whether different LPG sub-sectors are similar or different in reference to the model parameters estimated in the VLGC market.

Section 4.2 considers the dependency between LPG price spread and freight rate. In future research, to understand traders' arbitrage economics and help traders for decision makings regarding whether to move the cargo between regions, the dependency between the absolute arbitrage economics (spread – cost of transportation) and oil prices can be examined.

Section 4.3 uses a single freight rate to represent freight rate movements for different routes, as the Baltic index only has one LPG route available. However, rates on individual routes may not follow exactly the same pattern in the short run. Furthermore, a more detailed database which separates spot and contract fixtures may yield interesting results. For future research, owners' destination choice regarding where to load the cargo can be modeled to better understand the owners' behavior.

For Chapter 5, the scope of research is limited to the product tanker market itself. The dependency between product tanker rates and crude oil tanker rates can be a future research direction, as the two markets are often closely related and switch-over activities from carrying clean cargoes to crude oil exist in the product tanker market.

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