DEPENDENCE AND VOLATILITY SPILLOVER AMONG CHINESE SHIPPING STOCK SECTOR INDEX, OIL PRICE, OCEAN FREIGHT CHAREG AND EXCHANGE RATE

ZITONG ZHAO

MASTER OF ECONOMICS

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GRADUATE SCHOOL
CHIANG MAI UNIVERSITY
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ZITONG ZHAO

A THESIS SUBMITTED TO CHIANG MAI UNIVERSITY IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF ECONOMICS

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THIS THESIS HAS BEEN APPROVED TO BE A PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF ECONOMICS

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Zitong Zhao

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หัวข้อวิทยานิพนธ์	การขึ้นอยู่แก่กันและผลกระทบข้างเคียงความผันผวนระหว่างดัชนีหุ้นภาคการขนส่งของจีนราคาน้ำมัน ค่าระวางเรือและอัตราการแลกเปลี่ยน
ผู้เขียน	นางสาวจื่อถง จ้าว
ปริญญา	เศรษฐศาสตรมหาบัณฑิต
คณะกรรมการที่ปรึกษา	รศ.ดร.เริงชัย ตันสุชาติ อาจารย์ที่ปรึกษาหลัก อ.ดร.ภารวี มณีจักร อาจารย์ที่ปรึกษาร่วม อ.ดร.วรพล ยะมะกะ อาจารย์ที่ปรึกษาร่วม

บทคัดย่อ

บทความนี้ใช้โมเดลคอปูล่าแบบหลายตัวแปรและแบบจำลอง VAR เพื่อประเมินการพึ่งพาและความผันผวนของดัชนีหุ้นภาคการขนส่งซึ่งวัดโดยดัชนีภาค SSE (ตลาดหลักทรัพย์เซี่ยงไฮ้) ราคาค่าขนส่งพานาแม็กซ์โดยเฉลี่ย 4 เส้นทางเส้นทางหยวน / อัตราแลกเปลี่ยนที่กำหนด RMB/USD และราคาน้ำมันล่วงหน้าของ WTI ในการทำเช่นนี้การวิจัยประกอบด้วยสองส่วน

เพื่อวิเคราะห์ความสัมพันธ์และความผันผวนของตลาดทั้งสี่เหล่านี้ อันดับแรกเราใช้แบบจำลอง ARMA-GARCH เพื่อหาปริมาณการกระจายระยะขอบและความผันผวนตามเงื่อนไข จากนั้นเราใช้โมเดลคอปูลาหลายตัวแปรเพื่อเชื่อมโยงการแจกแจงส่วนเพิ่มเพื่อวิเคราะห์การพึ่งพาระหว่างสี่ตลาด แบบจำลองคอปูลาสามารถวิเคราะห์การกระจายหลายตัวแปรและให้ความยืดหยุ่นมากกว่าวิธีการแบบดั้งเดิม และทำการวิเคราะห์ผลกระทบการรั่วไหลของความผันผวนโดยใช้แบบจำลอง VAR ฟังก์ชั่นตอบสนองต่อแรงกระตุ้นและการสลายตัวของความแปรปรวน

ผลการศึกษาแสดงให้เห็นว่าคอปูลาแบบปกติเป็นรูปแบบการพึ่งพาอาศัยที่เหมาะสมที่สุดเนื่องจาก AIC และ BIC นี้มีค่าต่ำที่สุดเมื่อเปรียบเทียบกับแบบจำลองคอปูลาอื่น ค่าสัมประสิทธิ์สหสัมพันธ์แสดงความผันผวนที่อ่อนแอขึ้นอยู่กับการพึ่งพาระหว่างสี่ตลาดเหล่านี้ นอกจากนี้ผลของ VAR ยังแนะนำให้มีการรั่วไหลของหุ้นขนส่งและฟิวเจอร์สน้ำมันต่อตลาดค่าระวางเรือ ผลลัพธ์ของฟังก์ชันตอบสนองต่อแรงกระตุ้นนั้นความผันผวนในตลาดทั้งสี่มีขนาดเล็กลง การค้นพบนี้อาจสะท้อนให้เห็นว่าตลาดทั้งสี่เหล่านี้อาจไม่ได้มีบทบาทนำเข้าซึ่งกันและกัน

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Thesis Title Dependence and Volatility Spillover Among Chinese Shipping Stock Sector Index, Oil Price, Ocean Freight Charge and Exchange Rate

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Degree Master of Economics

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ABSTRACT

This paper employs the multivariate copula model and VAR model to estimate the dependence and volatility spillover among shipping sector stock index which is measured by SSE (Shanghai stock exchange) sector indices, Panamax freight price as measured by average chartering of 4 routes, the RMB/USD nominal closing exchange rate and WTI oil futures price. In doing so, the research consists of two parts.

To capture the correlation and volatility spillover among these four markets. First, we employ the ARMA-GARCH model to quantify marginal distributions and conditional volatilities. Afterward we use a multivariate copula model to link marginal distributions to analyze the dependence among the four series. The copula model can be easily used to obtain multivariate distributions and offer more flexibility than traditional methods. Finally, we apply the VAR model, impulse response function to study the volatility spillover effects.

The empirical results show that the Gaussian copula is the most appropriate dependence model as the AIC and BIC of this copula are the lowest when compared to other candidate copula models. The dependence correlation coefficients show a weak volatility dependence among these four markets. In addition, the results of the VAR model imply a spillover effect from shipping stock and oil futures to the freight market.

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The consequence of impulse response function receipt that the volatility in the four markets exhibits a smaller in magnitude. This finding may reflect that these four markets may not play an import role in each other.

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CHAPTER 1

Introduction

1.1 Principle and Rational Backgrounds

In the present day, the shipping sector, oil, freight and currency act a pivotal part in China's economy. In the context of economic globalization, interactions among markets are becoming closer. China is a major export country and has the third-largest commercial fleet. China's shipping prosperity index has risen around 119.94 points since 2010, and the overall index broke through 1,500 points in the fourth quarter in 2017. This indicates the substantial growth of China's shipping sector in this decade which corresponds to the high growth of China's economy.

Table 1.1: Proprietary of world fleet, 2017

Rank (dead-weight tonnage)	Country or territory	Number of vessels	Dead-weight tonnage	Rank (dollars)	Total value (million dollars)
1	Greece	4,199	308,836,933	3	72,538
2	Japan	3,901	223,855,788	2	77,898
3	China	5,206	165,429,859	4	65,044
4	Germany	3,090	112,028,306	8	38,412
5	Singapore	2,599	930,629,750	7	39,193
6	Hong Kong (China)	1,523	80,976,874	9	25,769
7	Republic of Korea	1,656	67,100,538	11	20,928
8	United States	2,104	51,824,489	1	96,182
9	Norway	1,842	48,059,392	5	58,445
10	United Kingdom	1,360	46,864,949	6	40,617

Source: Clarksons Research (2017)

In Table 1.1, in terms of cargo capacity (309 million deadweight tonnes), Greece remains the largest country with ship-owing, followed by Japan, China, Germany, and Singapore. Jointly, half of the world's tonnage is controlled by these five countries (Table 1.1). In the terms of ship numbers, China is the dominating ship-owning country

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(5,206 ships with a gross tonnage of 1,000 tons or more). These include many smaller ships disposed of coastal shipping.

Over the past two decades, as China has become a global export giant, it has provided an important foundation for its maritime development (CMSI, 2013). The high-speed growth and expansion of China's shipping industry have made an important contribution to country's GDP growth (CRI English, 2010). China played an important role in the historical boom of the shipping market starting from the second half of 2002. The reason is that 84% of the goods are transported by shipping. China's international marine ships account for 5.3% of the total volume of the world merchant fleet

This research is about the relationship among shipping market and other related markets. Then the following parts on the rationality of markets selection include not only current situation of each market, but also correlation among them.

1.1.1 Rational of Sector Selection

Table 1.2: Operation of shipping listed companies, 2016-2017

Company	Turnover				Margin			
	2016 (Billion dollars)	Growth rate	2017 (Billion dollars)	Growth rate	2016 (Billion dollars)	Growth rate	2017 (Billio n	Growth rate
Chang Jiang Shipping Group Phoenix Co.	1.0	-7.5%	1.3	22.9%	-0.014	-1.92%	0.1	_
China Ocean Shipping (Group) Co .	18.7	1.8%	12.7	-32.1%	2.759	393%	1.6	-43.9%
Antong Holdings Co.	5.5	338%	9.3	70.6%	0.575	25.0%	0.8	41.4%
COSCO Shipping Specialized Carriers Co.	8.5	-14.0%	9.7	15.1%	0.072	6.6%	0.4	387.0%
Ningbo Marine (Group) Co.	1.6	8.1%	2.3	39.9%	0.129	4.5%	0.2	85.5%
China Merchants Shipping Co.	8.7	-2.1%	8.9	2.9%	2.486	50.0%	1.0	-60.3%
China COSCO Holdings Co.	102.3	23.8%	138.6	35.5%	-14.240	_	3.9	127.7%
Bohai Ferry Group CO.	1.8	3.5%	2.3	29.79%	0.316	3.0%	0.5	59.0%
Total	149.0	18.1%	184.5	23.80%	-7.644	-349%	8.4	—

Source: Shanghai Stock Exchange official website

We can see from Table 1.2, shipping listed companies in SSE A shares turned losses into profits. And the international shipping industry has been recovering

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since 2017. Turnover of 9 domestic shipping listed companies was \$18.445 billion dollars, up 23.8% year-on-year, and up 5.7 percentage points from the previous year. In terms of margin, it turned from a loss of \$764.4 million last year to a profit of \$842.8 million. Shipping stock sector turnover and revenue increased by 19.1% and 17.2% respectively over the same period, which is better than the average level of listed companies in SSE A shares.

With the evolution of the shipping industry, there are many shipping companies listed in China's stock market. But the shipping industry is a high-volatility and high-risk industry. The impact of global economic fluctuations is enormous in the shipping market (Lin Jing, 2016). Shipping enterprise operating performance is immediately following the change of global trade and other related industries. China's shipping companies have generally been weak in adapting to market volatility. Most of these firms are not good at stabilizing and adjusting their businesses to deal with the volatility. And between the booms and down period, their profits vary widely. These show their weakness in risk management. (China Daily, 2013).

Based on the following considerations, we decided to conduct research on China's shipping stocks sector. First, under the influence of periodicity and structural, the international shipping market generally recovered in 2017. Demand exceeded supply, and reducing overcapacity, which led to the growth of China's shipping industry. This is good news for importers, exporters, shipowners, and investors. Secondly, the level of shipping companies' development is uneven. Using the stock sector can fully describe the overall situation. Volatility brings uncertainty and risk to the shipping industry, which requires us to conduct quantitative analysis to provide crucial information for seeking out profits and avoid loss. Based on this situation, the study of the relationship among the shipping stocks sector and other related markets is important. **How to deal with so many uncertainties and how to measure correlation?** These problems are meant for us to study especially for those enterprises and investor.

1.1.2 Rational of Oil Market Selection

In addition, as an important factor that affects the cost and profit of shipping, oil has played an important part in most of the economics in the world as well as in China. Its demand and supply will contribute a direct and potential impact on markets.

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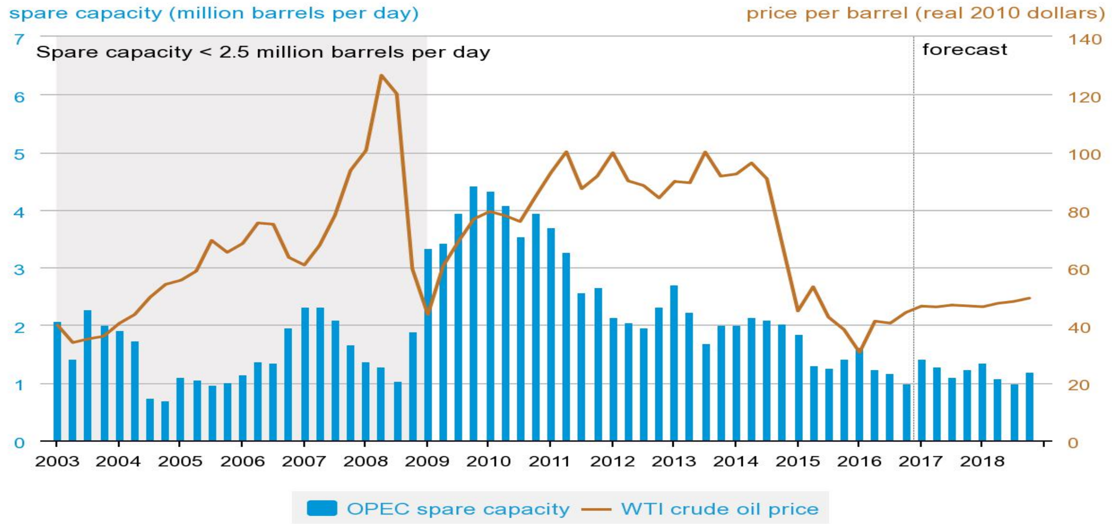
Crude oil futures are a type of futures contracts. It is coordinated by oil buyers and sellers and agrees to deliver a given amount of physical crude oil on a specific date in the future. Since the advent of crude oil futures, the volume of transactions has increased rapidly. Nowadays, it has become an important part of the futures market. The main function of crude oil futures is to evade wind inspection and sell or buy crude oil futures by the anticipation of the future price of oil.



Source: U.S Energy Information Administration, Thomson Reuters, 2018

Figure 1.1:OPEC spare production capacity and WTI crude oil price, 2003-2018.

Figure 1.1 displays that the price of crude oil in 2003 was 40 dollars a barrel, and it exceeded U.S. $60 a barrel in 2005. In the financial crisis of 2008-2009, oil prices fell sharply after peaking at a record $137.27 on July 11, 2008. A supply glut caused by multiple factors spurred a sharp drop in oil prices that lasted until February 2016. Consequently, the link between oil and oil-related industries are strengthened because of this volatility.

The operating performance of shipping companies in various shipping markets and the change of freight rates are affected by the rise in oil prices. Higher oil prices translate into higher operating costs, which will eat into shipping companies' profits without a higher percentage of freight costs. However, the operating margin is one measure of profitability. Investors like to see strong performance in relation to profit: typically some of that profit gets shared out between the owners of the company. This profit is called the dividend. They will increasingly be attracted to buying shares of companies if they expect to increase the dividend payment. If increasing the numbers of

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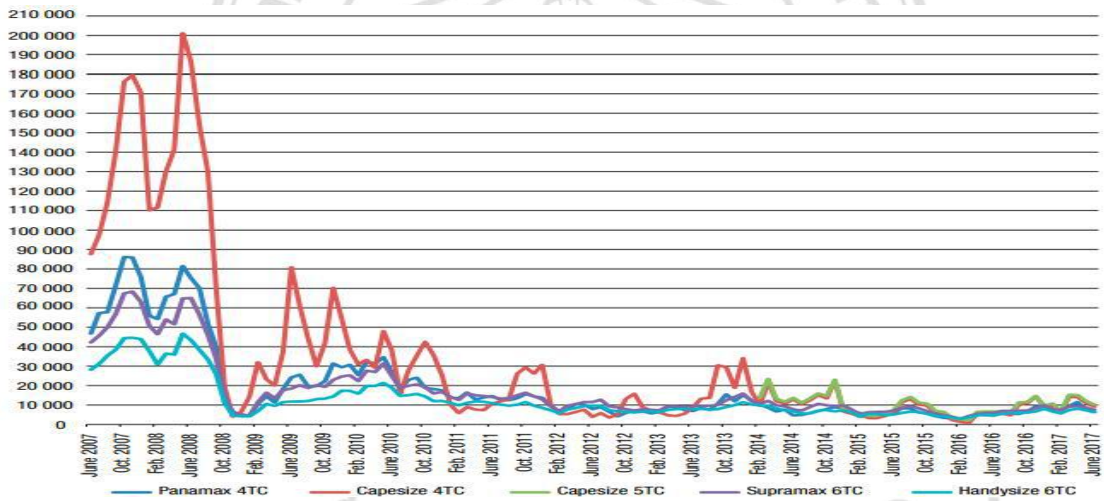
people attempt to buy the stock then the overall demand for the stock will increase and this will raise up the price of the stock. So in summary, the increase in dividends is indicated by strong operating margins. This may raise the price of the stock or increase demand for the company's stock.

1.1.3 Rational of Shipping Freight Selection

Freight rate is another factor that affects an import and export volume. It shows significant volatility in recent years. The cheapest trade route is the sea, and maritime routes have completed 2/3 of the world's total cargo trade. This is enough to show the importance of its existence to every maritime nation. The way supply capacity management is handled still determines freight rates, given the uncertain global demand for seaborne trade.



Source: Cass Information Systems Inc, 2017

Figure 1.2: Daily rate of vessels, 2007-2017 (Dollars per day).

Figure 1.2 illustrates that the average of four charter routes for the panamax ships on the Baltic Exchange in 2016 was about $5,615 per day. The Panamax ships saw a slight improvement in profits in late 2016 and early 2017, helped by an expanding fleet and seasonally strong grain shipments from South America, as well as a steady increase in the coal trade. Obviously, the shipping industry is interaction between supply and demand to decide the freight rate, which is a typical cyclical industry.

Freight rates, in their turn, are the basic exchange commodity, and the prices depend on other exchange commodities such as oil (Alizadeh and Muradoglu, 2014). Limited by the existing technology and costs, effective energy alternatives (e.g. biofuels,

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solar and wind) have yet to be adopted. As with other models, sea transport relies heavily on oil for propulsion. For developing countries, the impact of rising and fluctuating oil prices for transport costs and trade is significant.

In today's global economy, international trade ties economies together. Information about the economic activity is reflected in shipping rates, which are reflected in stock prices. Changes in shipping freight rates can affect the cash flow of shipping listed companies and their stock price.

1.1.4 Rational of Exchange Rate Selection

The U.S. and China have the world's largest economies, so the dollar-yuan conversion has become one of the most closely watched exchange rates.

Source: Bloomberg.

Figure 1.3: Exchange rate: China Yuan to dollars, 2017-2018.

From Figure 1.3, in 2017, the yuan rose 8 percent. In June and July 2018, the yuan is weakening, the dollar is strengthening. On the other hand, a weaker yuan would translate to higher prices for consumers of foreign-produced goods. On the positive side, the depreciation of the yuan will benefit China's internal market for products facing foreign competition. It would also make China's exports more competitive. Because the shipping sector relies mainly on domestic rather than foreign demand, exchange rate fluctuations are positively correlated with unexpected operating profits. Exchange rate changes may lead to exchange rate losses and profit decreases.

Because rising domestic stock prices can trigger currency adjustments. This is to accommodate changes in the demand and supply for domestic and foreign assets

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contained in an internationally diversified portfolio. So varies in stock prices affect the exchange rate. The decrease (increase) of the cash flow of domestic companies and their international competitiveness are affected by the appreciation (depreciation) of the reduces (increases) of the domestic currency. Thus reducing (increasing) domestic stock prices, exchange rate volatility will have an impact on stock prices. Today the common denomination used for international trading purposes is the dollar so the exchange rate also affects shipping costs. The ocean freight charge depends on exchange volatility and therefore is likely to be levied at the latest prevailing exchange rates.

Many internal and external driving factors that affect the operation, development, and direction of the shipping industry are important reasons for the fluctuation of the shipping industry. The whole world and the whole world trade in the oceans and other sectors is determined by supply and demand relations and market prices, which is why it is important to understand these relations and interactions well. For example, the freight rate directly affects the shipping company's income and profitability. Another important factor is oil prices. The bunker fuel cost affects the profit margins of shipping companies. Fuel costs account for 60% of the total operating costs of ships (according to the type of ship and service). If oil prices rise, it will further increase the operating costs of already high shipping companies, the rise in oil price not be taken lightly. The relationship between the exchange rate and the shipping stock sector cannot be ignored. The exchange rate fluctuation can be viewed as a factor which affects the freight rate in the U.S. dollar in term of the cost of transportation. As we mentioned above, it seems to have an economic relationship among China's shipping stock sector, shipping freight, currency, and oil markets.

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To sum up, a study of dependence and volatility spillover among China's shipping stock sector index, oil market, ocean freight market, and currency market is motivated by the following considerations. First, as we mentioned above, in this decade the substantial growth of China's shipping sector which corresponds to the high growth of the China's economy. China is a major export country and has the third largest commercial fleet. However, China's shipping financial market lacks the literature analysis. The study will provide useful information for investors, shipping owner, and financial institutions. Second, in the present day, the shipping sector, oil, freight and currency act a pivotal part in the China's economy. In the context of economic globalization, interactions among markets are becoming closer. An understanding of the relationship among these markets becomes important in particular for global investors. Lastly, market characteristics, for example, high volatility of markets. The volatility is synonymous with risk. It makes the study of these markets illuminating with regard to minimizing the risk and loss of investment.

1.2 Purpose of the Study

This study aims to analyze the dependence and volatility spillover among four stock markets consist of China's shipping sector stock index, oil futures, shipping freight, and currency market.

1) To study the characteristics, current situation of the shipping sector, oil futures market, freight market and currency market.

2) To analyze the dependence among these four markets (shipping sector, oil futures, freight, and currency) to investigate the relationship and the linkage among them.

3) To examine the volatility spillover among the China's shipping stock sector, oil futures market, shipping freight market and currency market.

1.3 Advantage of the Study

Unlike the existing studies, we rather investigate the volatility relationship and spillover effects among these variables. Apart from price and return time series relationship analyses that have a majority in recent studies, the time series relationship among volatility of the among China's shipping sector stock, shipping freight, currency and oil markets also deserves an examination because volatility transmission among the four markets seems to be important and common way that explains the flow of information among these markets.

1) This study is helpful for the investors, shipowners, ship operators, charterers, and financial institutions about what factors can affect the shipping sector and how to make the decision about investing in the portfolio.

2) The result of dependence may provide useful information for other researchers who want to study risk in other markets.

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3) The spillover measures provide important information for monitoring the risk of the financial crisis over time and provide crucial information for explaining the contagion mechanism for both investors and stock institutions.

1.4 Scope of the Study

The scope of this study is based on the price volatility of four markets which are China's shipping stock sector, oil market, shipping freight market, and currency market. The range of time period covers from 1_{st} January 2007 to 30_{th} March 2018. Employing the ARMA-GARCH model and multivariate copula model to capture the correlation among them. Next, we examine the volatility spillover effects using the VAR model, impulse response function.

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CHAPTER 2

Theoretical Foundation and Literature Review

2.1 Economic Theory

2.1.1 Financial Spillover Theory

From the perspective of the development of economic theory, it is currently inclined to explore two aspects, one is externalization and the other is internal. Spillover is one of the manifestations of economic externalize. The spillover theory also reflects the critical turn of economic theory. There are two types of spillover effects, mean spillover and volatility spillover, both of which refer to the appearance of information transmission between financial markets that can be observed.

The basic idea of resorting to real channels of contagion and spillover explains the propagation of shocks between countries (Perrico and Strasia, 2003). In general, this theory means that volatility increases the spread of shocks between countries. The financial perspective is mainly focused on the constraints and inefficiencies of the banking sector and the international stock market. The idea behind this channel is that the imperfections of the financial system will intensify during the crisis. Financial services are limited by this imperfect system to the extent that they can be provided to different countries that might previously be considered independent. In the most models, trade channels and other basic channels are closed. In other words, the theory based on financial linkages assumes that there is no real connection, and the only reason for shock propagation is that financial markets are subject to various restrictions and are not perfect. Obviously this is an extreme assumption, but allows a clearer analysis of the reasons behind the transmission mechanism.

Finally, the network can be used as a carrier of communication (Allen and Gale, 2000). The new theory of financial spillovers emphasizes networks across financial institutions. Elliott, Golub, and Jackson (2014) formed that first attempt at the

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theoretical basis of contagion through the Internet.

2.1.2 Dependency Theory

Raul Prebisch (1959) mentioned that the dependency theory about the resources flow from a periphery of the poor or undeveloped state of many nations in the world to a core of wealthy state and it also explains how developing countries are dependent on delayed countries. The theory of economic dependence refers to the economic theory that studies countries or markets in the world that are economically related and dependent. It pays special attention to the sensitive reaction between the economic development of a country and international economic exchanges. Specifically, the term “dependence” has two meanings: on the one hand, the economic situation in other countries has a direct impact on the economic development of the country. On the other hand, the economic things that the country has to do depend to a certain extent on the actions and policies of other countries. This is the basic orientation and main content of this theoretical research.

The economic and trade dependence of countries in the world can be reflected in many aspects, including: (1) The dependence of economic and trade policies. Different systems, policies, and actual effects between countries may affect each other. This kind of influence often exceeds people’s prejudgment, so interaction and coordination between countries is necessary. (2) Dependence of economic and trade structures. This determines the respective economic and trade structure of these two countries and their dependence on each other, because both countries cannot develop their own economy effectively and continuously without importing a large number of competitive products from each other. (3) Dependence of economic and trade objectives. Sometimes a country needs or even relies on the cooperation and coordination of other countries in economic policies to implement its own economic and trade goals.

2.1.3 Stakeholder Theory

Stakeholders include the company’s shareholders, creditors, employees, consumers, suppliers and other trading partners, as well as pressure groups such as government departments, local communities, media and environmentalism, and even objects directly or indirectly affected by business activities such as natural environment and human descendants. Some of them share operational risks of enterprise, some pay a

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price for the enterprise's operational activities, some supervise and restrict the enterprise, and the enterprise's operational decisions must consider their interests or accept their constraints Friedman (2006).

The theory of stakeholder also has defects and deficiencies. (1) The definition of stakeholders is too broad, and where are the boundaries of stakeholders? Although many experts and scholars have elaborated their views on the definition and division of stakeholders, most of them only stay at the stage of discussion and hypothesis. (2) According to the traditional enterprise theory, the only goal of an enterprise is to "maximize economic profits". In addition to economic objectives, enterprises must also assume social and political responsibilities. This will make the behavior of the enterprise limited by the framework, and the result is likely to lead to the loss of the economic profit of the enterprise. (3) How to apply stakeholder theory to practice? Many scholars have analyzed and discussed the feasibility of stakeholders from various aspects, and theoretically proved that the theory of stakeholders relevance is feasible.

2.2 Econometric Theory

2.2.1 Auto-Regressive and Moving Average Model (ARMA)

The autoregressive moving average model (ARMA Model) is an important method to analysis time series. It is composed of two polynomials, one for the auto-regressive (AR) and the second for the moving average (MA). In time series, it's used to understand and predict future values.

The AR(p) refers to the auto-regressive model of order p:

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t, \qquad (2.1)$$

where c is a constant term, $\varphi_i,...,\varphi_p$ are parameters, ε_t is the white noise. $E(\varepsilon_t)=0$, $Var(\varepsilon_t)=\sigma_t^2>0$. Firstly, the parameters of this model need to be constrained in order to keep the model stationary. For example, process in the AR(1) model with $|\varphi_1|\geq 1$ are not stationary. The AR model describes the relationship between the current value and history value.

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The MA(q) refers to the moving average model of order q:

$$X_t = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_t \varepsilon_{t-i}, \tag{2.2}$$

where $\theta_1, ..., \theta_q$ are the parameters, μ is the expectation of X_t . $\varepsilon_t, \varepsilon_{t-1}, ...$ are white noise error terms. The MA model is stationary in any conditions. The MA model describes the error accumulation of auto-regressive part.

The ARMA(p,q) refers to the model with p auto-regressive terms and q moving-average terms showed as follows:

$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_t \varepsilon_{t-i}, \tag{2.3}$$

2.2.2 Generalized Autoregressive Conditional Heteroskedasticity (GARCH)

In economics, the AutoRegressive Conditional Heteroskedasticity (ARCH) model are proposed by Engle (1982) is used to characterize and model observed time series. It solves the issue of second assumption (constant variance) that traditional econometric on time-series variables. The variance over time is a linear combination of the squares of noise values in the past finite terms (i.e., autoregression). Thus, the autoregressive conditional heteroscedasticity model is employed commonly in modeling. Regression analysis and forecasting financial time series that exhibit time-varying volatility clustering.

Modeling a time series by an ARCH process:

$$\varepsilon_t = \sigma_t z_t, \tag{2.4}$$

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where ε_t is the error terms (return residuals, with respect to a mean process). These ε_t are split into a stochastic piece z_t and a time-dependence standard deviation σ_t characterizing the typical size of the terms. The random variable z_t is a strong white noise process.

The series σ_t^2 is modeled by:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + ... + \alpha_q \varepsilon_{t-1}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2, \tag{2.5}$$

where, $\alpha_0 > 0$ and $\alpha_i \geq 0$, $i > 0$.

The mean equation of ARCH(q) is:

$$Y_t = \beta X_t + \varepsilon_t , \tag{2.6}$$

where Y_t is the dependence variable, X_t is the independence variables.

If the model is generalized auto-regressive conditional heteroskedasticity (GARCH, Bollerslev (1986)) model, an auto-regressive moving average model (ARMA model) is supposed for the error variables. Compared with the ARCH model, the advantage of GARCH model is that a relatively simple GARCH model can be used to represent a high-order ARCH model, which makes it easier to identify and estimate the model. It is especially suitable for the analysis and prediction of volatility clustering, in the real world, such as stock price, exchange rate, inflation, and other financial time series usually show cluster fluctuations. This phenomenon is manifested in the fact that for a long period of time, its price has fluctuated greatly, and then it will remain relatively stable for the next period of time. Therefore, this model is particularly suitable for the analysis and forecasting volatility which is a very important guiding role for investors decisions. It’s significant often exceeds the value itself for analysis and forecasting.

The GARCH (p,q) model is shown as follow:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + ... + \alpha_q \varepsilon_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + ... + \beta_p \sigma_{t-p}^2 , \tag{2.7}$$

$$= \alpha_0 + \sum_{i=1}^{q} \alpha_1 \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_t \sigma_{t-i}^2 , \tag{2.8}$$

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2.2.3 Copula Theory

Sklar (1959) first introduces copula and Joe (1997) and Nelsen (2006) give a comprehensive study on it. The copula is applied in many industries. For example, in finance copula is used in derivative pricing, credit rating, market risk modeling, and asset allocation.

Copulas were invented in 1959 and are popular in high-dimensional statistical applications because they allow the modeling of random vectors to be easily model and estimated by separately estimating boundaries and dependencies. There are many parameters available for the copula series, which typically have parameters that control dependency intensity. The copula is mathematical tool that used in financial to determine economic capital adequacy, market risk and so on (Nelsen, 2005). The correlation coefficients are usually used to calculate the dependence between the returns of two or more assets.

First, the Copula function does not limit the choice of edge distribution, and can use a marginal multivariate distribution. Secondly, when building a model, we can study the marginal distribution of random variables and the related structures between them. Their dependence structure can be described by a Copula model, which makes the modeling simplified and easy to understand.

Suppose a random vector $(X_1, X_2, ..., X_n)$ its margins are continuous and uniformly distributed as:

$$(X_1, X_2, ..., X_n) = (F_1(X_1), F_2(X_2), ..., F_n(X_n)), \tag{2.9}$$

The copula of $(X_1, X_2, ..., X_n)$ is defined as the joint cumulative distribution function of $(U_1, U_2, ..., U_n)$. It can be written as:

$$C(U_1, U_2, ..., U_d) = \Pr[U_1 \le u_1, U_2 \le u_2, ..., U_n \le u_n], \tag{2.10}$$

Let F be a joint cumulative distribution function of n-dimensional variables, where the marginal cumulative distribution function of each variable is denoted as F_i. Then the copula function C is unique. Otherwise, the copula function C is only uniquely determined within the value range of each marginal cumulative distribution function.

The importance of the above is that according to Sklar's Theorem, the univariate margins and the dependence structure can be isolated from the joint distribution functions.

That is, given a procedure to generate a sample $(U_1, U_2, ..., U_n)$ from the copula distribution.

The corresponding copula could be determined by following equation as:

$$(X_1, X_2, ..., X_n) = (F_1^{-1}(U_1), F_2^{-1}(U_2), ..., F_n^{-1}(U_n)), \tag{2.11}$$

where,the inverses F_i^{-1} are unproblematic as F_i was assumed to be continuous.

$$C(U_1, U_2, ..., U_n) = \Pr[X_1 \le F_1^{-1}(U_1), X_2 \le F_2^{-1}(U_2), ..., X_n \le F_n^{-1}(U_n), \tag{2.12}$$

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2.2.4 VAR Model

Vector autoregressive model (VAR model) is a commonly used econometric model proposed by Christopher Sims, 1980. It's an extension of the AR model. The VAR model is used to estimate the dynamic relationship of joint endogenous variables without any prior constraints.

The characteristics of VAR model are: (1) There are only two things to be clear in the modeling process: The first is which variables are related to each other, and the related variables are included in the VAR model, The second is to determine the lag period k. The model can reflect most of the interaction between variables. (2) The VAR model imposes no zero constraint on parameters. (3) One of the applications of the unconstrained the VAR model is forecast.

VAR model is based on auto-regressive model. The auto-regressive model with degree k or AR(k) is shown as:

$$y_t = \phi_0 + \phi_1 y_{t-1} + \ldots + \phi_k y_{t-k} + \varepsilon_t , \tag{2.13}$$

VAR model with degree k or AR(k) is shown as:

$$y_{i,t} = \phi_{i,0} + \sum_{j=1}^{k} \phi_{1,ij} y_{1,t-j} + \ldots + \sum_{j=1}^{k} \phi_{m,ij} y_{m,t-j} + \varepsilon_{i,t} , \tag{2.14}$$

where $y_{i,t}$ is an $N \times 1$ order time series column vector. $\phi_{i,0}$ is an constant term. Furthermore, $\phi_{1,ij}$ is represented to a coefficient of variable i that regresses on variable i with lag j . $\varepsilon_{i,t}$ is generated from $y_{i,t}$ which is defined as a non-autocorrelated residual with zero mean.

2.2.5 Impulse Response Function

Ender (2004), the Impulse Response Function (IRF) is intended to measure the effect of any variable in model with other variables in the same period and in the future that the shocks or impulse in the VAR model is stochastic error term.

The change of the sequence order of the variable in impulse response function will produce different impulse images. It is the response of the linear system to the unit pulse input signal with the initial condition equal to zero. If the impulse function is used as the input of the system and the response of the system is measured,

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all the information about the dynamic characteristics of the system can be obtained. In practice, pulsating input signals with much shorter duration can be regarded as impulse signals compared with the time constant of the system.

$$x_t = \mu \sum_{i=0}^{\infty} \phi_i \varepsilon_{t-i} \tag{2.15}$$

where, equation (2.15) is equation represent Moving Average Representation of y_t and z_t and set of coefficient ϕ_t.

2.3 Definition

2.3.1 Definition of Spillover Effects

Spillover effect refers to the interaction between two series. In economics, the spillover effect refers to the economic events in one context, which will not only produce the expected effect of the activity but also have an impact on people or society outside the organization. Spillover effects are divided into two categories: mean spillover and volatility spillover. A mean spillover is the impact of a change in one market's price or return on another market. Volatility spillover is the impact of changes in one market's volatility (usually measured by variance) on other markets. According to the efficient market hypothesis of financial markets, any information related to financial markets will be digested by all financial markets simultaneously in the fastest time and reflected in the price (Zhengde Xiong, 2015). It means prices in every financial market follow a random walk, and market returns can show white noise.

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2.3.2 Definition of Dependence

Economic dependence refers to the interdependence of countries, economies, and markets for economic and non-economic reasons. Dependency has always been a hot topic in statistical research. It is essentially a structural concept that reflects other values and thoughts. However, this phenomenon must be fully identified if it is to be understood correctly. Dependence captures the important structural relationships between many economies, nations, and nations with different economic, political, and military powers. But the effects of their interactions are continuous changes, inter temporal and spatial. The study of dependency is an important problem issue in the field of financial risk. Portfolio investment, asset pricing, the transmission of volatility and risk management are all related to dependency research.

2.3.3 Definition of A-Shares

There are A-shares, B-shares, H-shares, S-shares, N-shares, T-shares in Shanghai stock exchange. A-shares are denominated in RMB, in the face of China's citizens issued and listed in the territory of the stock.

2.3.4 Definition of Stock Sectors

The stock sector refers to the groups that constitute the stock market. Dividing the stock market into different sectors allows for a more in-depth analysis of the economy as a whole. Generally, the stock sector can be classified by the nature of industry, concept, market size, and region, then each made up smaller sectors. For example, in the industry-based sector, we can divide the market into ten genera. To be specific, these ten genera include agriculture sector, mining sector, manufacturing sector, hydroelectricity sector, constitution sector, wholesale and retail sector, transportation and storage sector, financial and real-estate sector, social organization and individual sector and some other unclassified activities. Each sector consists of many smaller particular sectors. The shipping sector belongs to the transportation sector.

2.4 Literature Review

2.4.1 Review of Dependence

2.4.1.1 Review the Correlation Among Stock, Freight, Oil and Exchange Rate

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In the previous literature, unrestricted dependence on exogenous has been studied by many scholars. These studies focus on estimating and understanding the links between two or more financial markets. Recent studies on dependence analysis have focused on the combinations of oil prices and futures prices, exchange rate or stock market combinations. **(see Martens & Poon, 2001; Antoniou, Pescetto & Violaris, 2003; Kim, Moshirian & Wu, 2006; Savva, 2009; Bhar & Hammoudeh, 2011; Lin, 2012)**.

There are a few kinds of literature related to the dependence of shipping. **Erdogan and Tata (2013)** estimates the returns of the Baltic Dry Index (BDI) and the Dow Jones Industrial Average (DJIA) to use multivariate copula models. From the research results, there is a significant dependence between the two markets. During the financial crisis, the dependence between these two markets will become stronger. They also found that, based on market-specific conditions, the degree of information spillover between these two markets will change over time. There are researches on the correlation of stock price and oil futures which are similar to our research methods.

Different from previous methods **Wu and Chung (2011)** used the GARCH model based on dynamic copula to depict the tail characteristics of data and study the dependence between us dollar exchange rate and oil price. To estimate the relationship between the Vietnamese and China's stock markets **Nguyen and Bhatti (2012)** used nonparametric and copula methods. They observed a right-tail dependence between China's stock markets and international oil prices, while Vietnamese stocks show the opposite effect. As China's currency is managed rather than freely floated, this may affect the relevance of the market. **Liu and Wan (2012)** employing a cointegration test allowing for a structural break and using linear and nonlinear Granger causality tests to research the dependence of China Yuan exchange rates and the Shanghai stock exchange. The results show that there is a significant positive correlation between stocks and exchange rates after the financial crisis. But before the financial crisis, they did not find a causal relationship between exchange rates and stock prices.

2.4.1.2 Review the Method of Dependence

The majority of the studies considered using the GARCH-type model originated by **Bollerslev (1986).** There are many scholars began to test the existence of conditional heteroscedasticity in time series in the financial field, and most of them described the characteristics of financial asset price fluctuations, such as the clustering of fluctuations and the "sharp peak and fat tail" of distribution. **(Erb et al., 1994; Longin and Solnik, 2010; Ang and Chen, 2002)**. The assumption of normal distribution volatility and linear dependence structures would mislead us in modeling the co-movement between these markets.

The copula functions (based on the Sklar's theorem) have been becoming popular in modeling asymmetric dependencies structure in the field of finance. Thus, the more robust economic model presented in the modern literature is

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copula-GARCH model **(Lee and Lin, 2010; Wang et al., 2010; Wu et al., 2012; Weib, 2013; Shen et al., 2013; Riccetti et al., 2013)** All of these studies indicated that the dependence structures of economic variables are found to be asymmetric and the GARCH-type family is a dominant method.

Furthermore, **Bollerslev (1987)** suggested the use of conditional student-*t* distribution in order to capture the fat-tailed characteristics of financial returns data. There are several further distributions proposed subsequently such as the skewed student-*t* distribution by **Hansen (1994)** and sewed generalized error distribution by **Theodossion (2000)**. **Jondeau and Rockinger (2006)** found that the skewed student-*t* distribution well described the volatility of financial data than that normal while **Zhang (2009)** found that the skewed generalized error distribution best fits the data of German stock market. Thus, in this research, we will assume the conditional distributions of the GARCH model to be the skewed student-*t* distribution for the greater appropriateness of the method.

2.4.2 Review of Spillover Effects

One of the core issues of modern financial research is the volatility in the price of financial markets. **Lakshmi and Gamini (2004)** point out that volatility represents a risk. When financial markets fluctuate, especially large fluctuations, it will bring losses to market beneficiaries and risk-averse investors. **Ling and Gurjeet (2010)** found that in the past decade, volatility in financial markets has spread from one market to another, creating a phenomenon of “contagion”. A notable feature of this phenomenon is that even in a market where the correlation is not large under normal circumstances, it will be closely linked under the volatility of the market. Volatility brings risks to investment and uncertainty of relationship among markets that has implicated for investment decisions. Hence, the analysis of financial market integration, dependence and the degree of correlation between assets plays a vital role in many financial decisions for market participants such as international trading companies and financial institutions. For these reasons, the measurement and analysis of dependence and volatility spillover. It has become an important direction to study the relationship between financial markets. The theoretical and practical significance of these two research methods has begun to attract scholars’ attention.

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There are two categories to study the interactions between various assets or markets. One is the spillover effect between variables or markets, which reflects a relationship between variables, which is caused by the fluctuation of one of the variables. The spillover effect is divided into mean spillover and volatility spillover. Another, there are potential common factors in the market, which reflects a certain causal relationship between the markets, or people's common reaction to market fluctuations, which reflects the interrelationship between different markets.

Hoesli and Kustrim (2011) analyzed the relationships between sensitized real estate markets and common stock markets which used an asymmetric *t*-BEKK approach and a time-varying copula framework. They found that during the financial crisis, the spillover effects were significant both domestically and internationally in the United States. Further, dependency on tail distributions between markets appears to be quite important. **Yaqing and Hongbing (2014)** proposed the structure vector autoregressive model is used to study the spillover effect under information transfer and the dependence under the influence of the same external factors. Empirical results found significant volatility spillover and the dynamic conditional correlation between the residual series of the structural conditional correlation model for China and U.S. stock price returns especially in financial crises. **Ronald and Vasilios (2018)** used a multivariate GARCH model. This method is able to capture market dependence and volatility spillover effect, and can be used in both binary and multivariate studies. The above literature has done research on two aspects of spillover effect and common movement.

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2.4.2.1 Review the Relationship Among Stock, Freight, Oil and Exchange Rate

As mentioned before, the study of spillover effects between markets and the empirical study of international common movements across markets is one of the most important research contents of economists in the field of international finance and macroeconomics. There are many scholars who have studied the spillover effects across markets. **Jones and Kaul (1996)** test the international stock market (Canada, UK, Japan, and the U.S.) for the impact of oil price shocks was the first to use a standard cash flow dividend valuation model. They found that the impact of oil shocks on cash flows could explain the exchange rate markets in Canada and the U.S. reacted to oil price fluctuations **Papapetrou (2001) and El-Sharif et al., (2005)** proposed that oil price shocks have a negative and weak response on the non-gas or non-oil stock volatility. **Apergis and Miller (2009)** use the SVAR (Structural Vector Autoregressive) model to break down oil price changes into three parts of impact (oil demand, global aggregate demand, global oil supply) They study the effects of these three parts of the oil price on the stock prices of eight developed economies. The results show that the oil price has no significant effect on the stock price.

Other literature showing that the dependence between oil price and stock price include **(Arouri and Rault, 2012; Basher and Sadorsky, 2006; Broadstock, Cao and Zhang, 2012; Narayan and Gupta, 2015; Park and Ratti, 2008; Sadorsky, 1999)**. In general, these papers provide research ideas on the relationship between oil price changes and stock prices.

Zhao (2010) uses the monthly real data of the RMB effective exchange rate and stock price from January 1991 to June 2009. The multivariate generalized auto regressive conditional heteroskedasticity (GARCH) model and vector autoregressive (VAR) model are used to empirically analyze the dynamic relationship between these two variables. From the research results, there is no stable long-term relationship between the stock price and the real effective exchange rate of the RMB. **Yu and Liao (2017)** study the mean spillover effect and the volatility spillover effect among currency interest rate, stock return rate, and exchange rate. In order to study the spillover effect, the VAR model and asymmetric GARCH (1,1)-BEKK model were utilized. The results show that there is only a mean spillover effect from the money market to the stock market between the money market and the stock market.

The literature on the study of spillover effects between the maritime market and related markets has the following. **Ora and Karahasan (2013)** pointed out that there is a significant information spillover effect between the ocean freight charge market and the stock market. The research of volatility spillovers has significant meaning for investors, regulators, shipowners, lenders, charterers and other participants in financial markets.

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2.4.2.2 Review the Method of Spillover Effects

The vector autoregression (VAR) model in economics was made popular by **Sims (1980)**. The VAR model is a natural extension of the univariate autoregressive model and can be used to describe the dynamic behavior of the financial time series. Many kinds of research use the VAR model to study financial time series. The most popular one is the book of **Culbertson (1996)** which is about foreign exchange, bonds and stocks. The research on volatility spillover in the market relies on the vector error correction model (VECM) and the VAR model **(Li, 2007; Hassan, 2015). Zhao (2010)** resolved the relationship between the stock price returns and RMB real effective exchange rate using multivariate GARCH models and the VAR model. The results displayed that there are not exist a stable long-term equilibrium relationship between RMB real effective exchange rate and stock price. Furthermore, **Ernesto (2017)** used the transmission dynamics underlying the spillover effects by estimating various structural vector autoregressions (SVAR) in an emerging market economy. The analysis finds that U.S. monetary policy shocks are a significant determinant of Colombia's central bank policy rate.

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CHAPTER 3

Research Methodology and Data

3.1 Research Design

In order to study the dependence structure and volatility spillover among these four markets (shipping stock sector, oil futures, shipping freight, and currency), we use the following method.

1) Before the estimation of such a model, we should always check if the time series we analyze are stationary. In this study, we employ the ADF, PP and KPSS unit root test to check whether a series is stationary.

2) Dependence analysis: After testing for the stationary values, as the next step we estimate the volatility of each variable using ARMA(p,q)-GARCH(1,1) model with skewed student-*t*. First, We select the optimal lag for ARMA(p,q) by using the Akaike Information Criterion (AIC). Second, we use the KS-test to ensure the marginals are uniform distribution in $[0,1]$ and Box-Ljung test to confirm residuals are independent and identically distributed random variables $(i.i.d)$. Then, these marginal distribution from the ARMA(p,q)-GARCH(1,1) model are used as inputs to the copula function. We use the copula function to link the marginal distributions simultaneously in order to analyze the dependence structure among four variables. Moreover, a goodness of fit test based on Kendall's tau process will be employed to ensure the dependence structure of the data series is appropriate for a chosen family of copulas.

3) Volatility spillover analysis: We have used the GARCH model to measure the volatility of each variable before. Then, we use volatility inputs to the VAR model, impulse response function to calculate the direction and size of the correlation among four volatility after the shocks happened. We select the optimal lag for VAR(p) by using

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the Akaike Information Criterion (AIC).

3.2 Conceptual Framework

Figure 3.1 describe the conceptual framework. This study aims to analyze the co-movement and volatility spillover among four financial assets. The stock price which is measured by SSE (Shanghai Stock Exchange) shipping sector indices, oil futures as measured by WTI (West Texas Intermediate) oil futures price. The ocean freight charge as measured by the average of the Panamax ship chartering of 4 routes, the exchange rate is measured by the Renminbi (RMB) against the U.S. dollars nominal closing exchange rate. In order to find out the relationship among these four variables, we measure the dependence structure and volatility spillover to get the correlation coefficient and the parameter that capture the relationship among variables.

This figure illustrates that the first we use ARMA(p,q)-GARCH(1,1) model to quantify the marginal distributions and conditional volatilities. Second, from the empirical result, we can analyze the dependence between the four series by using a multivariate copula model to link the marginal distributions. Third, we capture the volatility spillover effects using the VAR model and impulse response function.

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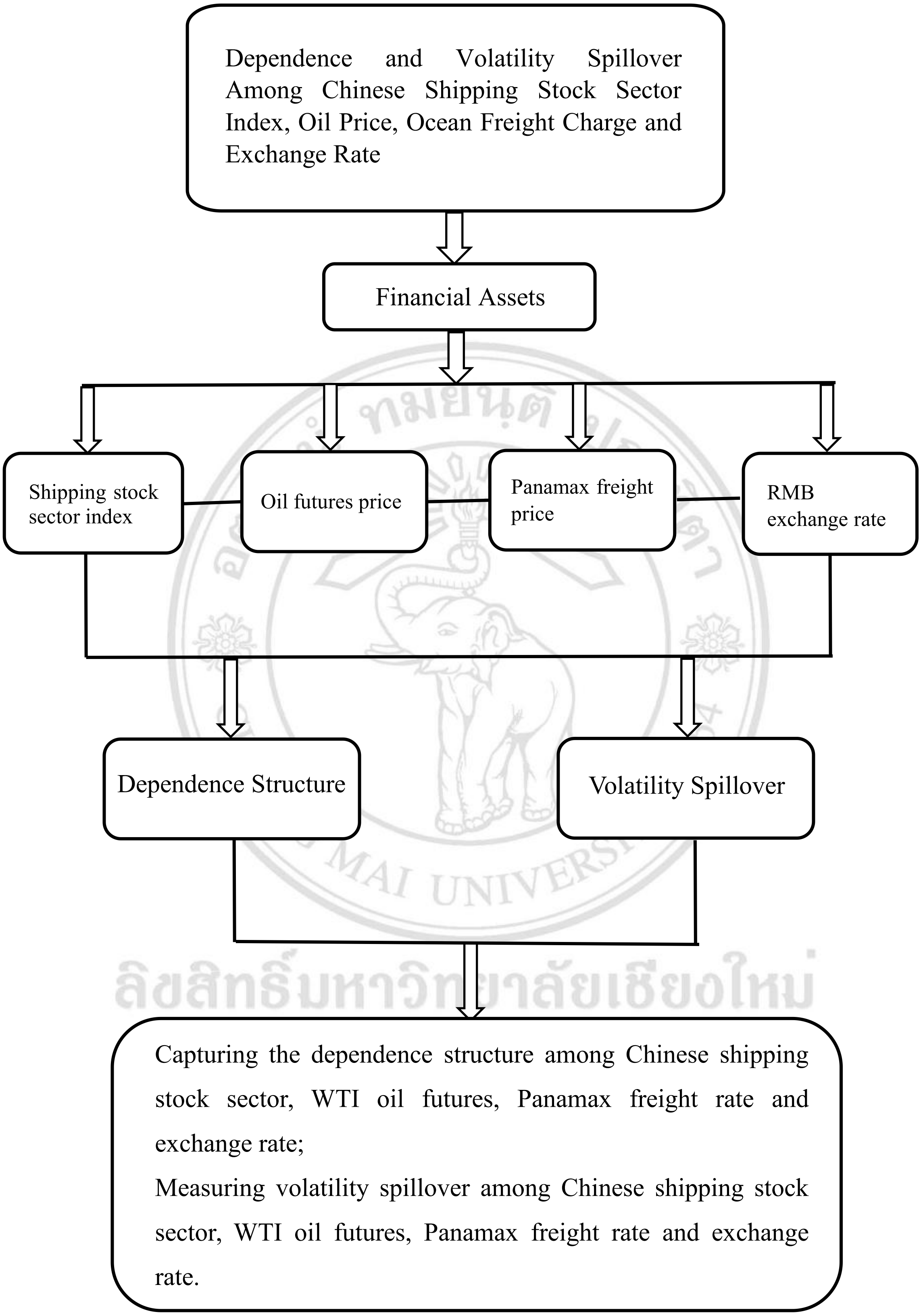

Figure 3.1: Conceptual Framework.

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3.3 Model Specification

This study concentrates on the dependence and volatility spillover study of these four markets (shipping stock sector, oil futures, shipping freight, and currency). The model used in the dependence study is ARMA(p,q)-GARCH(1,1) and multivariate copula model. And we capture the volatility spillover effects using the VAR model, impulse response function. The range of time period covers from 1$_{st}$ January 2007 to 30$_{th}$ March 2018.

In this study, an ARMA(p,q)-GARCH(1,1) model is considered as follows:

$$R_{f,t} = \varphi_0 + \sum_{i=1}^{p} \varphi_i R_{f,t-i} + \sum_{j=1}^{q} \theta_{f,j} \varepsilon_{f,t-j} + \varepsilon_{f,t}, \tag{3.1}$$

$$\varepsilon_{f,t} = h_{f,t}^{1/2} z_{f,t}, \tag{3.2}$$

$$h_{f,t} = \omega_0 + \alpha_1 \varepsilon_{f,t-1}^2 + \beta_1 h_{f,t-1}, \tag{3.3}$$

where, equation (3.1) is an ARMA (p,q) model. The volatility of return is explained through a univariate GARCH (1,1) process, described by (3.2) and (3.3).

$R_{f,t}$: the return of each random variables at time t, $f=1,2,3,4$. Namely: (1) Chinese shipping stock sector index (SI), (2) the Panamax freight rate (PF), (3) WTI oil futures (OF), (4) China Yuan against US dollars exchange rate (ER).

$\varepsilon_{f,t}$: error term of marginal distribution for each variable.

$z_{f,t}$: independent and identically distributed random variables ($i.i.d$) innovation variables that follows a skewed student-*t* distribution.

$h_{f,t}$: conditional variance of each variable from the GARCH model.

Next, we will receive the standard residual, which is $\varepsilon_{f,t}$ from each variable. Transfer residuals into uniform distribution in [0,1]. And substitute the marginals into the multivariate copula. Then we characterize the dependence structure among four markets.

The four-dimensional copula function is given by:

$$C(u_{SI}, u_{PF}, u_{OF}, u_{ER}) = H(F_1^{-1}(u_{SI}), F_2^{-1}(u_{PF}), F_3^{-1}(u_{OF}), F_4^{-1}(u_{ER})), \tag{3.4}$$

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where,

u_{SI} : cumulative marginal distribution of Chinese shipping stock sector index.

u_{PF} : cumulative marginal distribution of the Panamax freight rate.

u_{OF} : cumulative marginal distribution of WTI oil futures price.

u_{ER} : cumulative marginal distribution of China Yuan exchange rate against US dollars.

For the study of volatility spillover. We have used the GARCH model to estimate the volatility of each variable before. Then, we use volatility inputs as a variable in the VAR model to calculate the direction and size of the correlation among four volatility after the shocks happened.

A VAR model in four variables can be written in matrix form as:

$$\begin{bmatrix} h_{1,t} \\ h_{2,t} \\ h_{3,t} \\ h_{4,t} \end{bmatrix} = \begin{bmatrix} \varphi_1 \\ \varphi_2 \\ \varphi_3 \\ \varphi_4 \end{bmatrix} + \begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} & \alpha_{14} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} & \alpha_{24} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & \alpha_{34} \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} \end{bmatrix} \begin{bmatrix} h_{1,t-1} \\ h_{2,t-1} \\ h_{3,t-1} \\ h_{4,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \end{bmatrix} \tag{3.5}$$

where $\left(h_{1,t}, h_{2,t}, h_{3,t}, h_{4,t}\right)^{-1}$ denote an $(N \times 1)$ vector of conditional volatilities obtained form the GARCH process at time *t*, namely Chinese shipping stock sector index (SI), Panamax freight rate (PF), WTI oil futures (OF), China Yuan exchange rate (ER).

φ_0 : the deterministic components of the VAR system.

φ_i : $N\times N$ coefficient matrices.

$\varepsilon \sim (0,\Sigma)$: a vector of independently and identically distributed disturbances.

After doing VAR estimation, impulse response function can be applied to find out the effects over time of four variables. The impulse response function will describe the response over time of each variable in the VAR model to a one time shock in any given variable while all others are kept constant.

Represented by a matrix as:

$$\begin{bmatrix} h_{1,t} \\ h_{2,t} \\ h_{3,t} \\ h_{4,t} \end{bmatrix} = \begin{bmatrix} \varphi_1 \\ \varphi_2 \\ \varphi_3 \\ \varphi_4 \end{bmatrix} + \begin{bmatrix} \beta^{(1)}_{11} & \beta^{(1)}_{12} & \beta^{(1)}_{13} & \beta^{(1)}_{14} \\ \beta^{(1)}_{21} & \beta^{(1)}_{22} & \beta^{(1)}_{23} & \beta^{(1)}_{24} \\ \beta^{(1)}_{31} & \beta^{(1)}_{32} & \beta^{(1)}_{33} & \beta^{(1)}_{34} \\ \beta^{(1)}_{41} & \beta^{(1)}_{42} & \beta^{(1)}_{43} & \beta^{(1)}_{44} \end{bmatrix} \begin{bmatrix} h_{1,t-1} \\ h_{2,t-1} \\ h_{3,t-1} \\ h_{4,t-1} \end{bmatrix} + \begin{bmatrix} \beta^{(2)}_{11} & \beta^{(2)}_{12} & \beta^{(2)}_{13} & \beta^{(2)}_{14} \\ \beta^{(2)}_{21} & \beta^{(2)}_{22} & \beta^{(2)}_{23} & \beta^{(2)}_{24} \\ \beta^{(2)}_{31} & \beta^{(2)}_{32} & \beta^{(2)}_{33} & \beta^{(2)}_{34} \\ \beta^{(2)}_{41} & \beta^{(2)}_{42} & \beta^{(2)}_{43} & \beta^{(2)}_{44} \end{bmatrix} \begin{bmatrix} h_{1,t-2} \\ h_{2,t-2} \\ h_{3,t-2} \\ h_{4,t-2} \end{bmatrix} + \dots + \begin{bmatrix} \beta^{(p)}_{11} & \beta^{(p)}_{12} & \beta^{(p)}_{13} & \beta^{(p)}_{14} \\ \beta^{(p)}_{21} & \beta^{(p)}_{22} & \beta^{(p)}_{23} & \beta^{(p)}_{24} \\ \beta^{(p)}_{31} & \beta^{(p)}_{32} & \beta^{(p)}_{33} & \beta^{(p)}_{34} \\ \beta^{(p)}_{41} & \beta^{(p)}_{42} & \beta^{(p)}_{43} & \beta^{(p)}_{44} \end{bmatrix} \begin{bmatrix} h_{1,t-p} \\ h_{2,t-p} \\ h_{3,t-p} \\ h_{4,t-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \end{bmatrix} \tag{3.6}$$

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where $\left(h_{1,t}, h_{2,t}, h_{3,t}, h_{4,t}\right)^{-1}$ denote an $(N \times 1)$ vector of conditional volatilities obtained form the GARCH process at time *t*, namely Chinese shipping stock sector index (SI), Panamax freight rate (PF), WTI oil futures (OF), China Yuan exchange rate (ER). Error vector ε is white noise.

3.4 Data

All the data to be used in econometric models are taken from the Thomson Reuters Data Stream database and Wind database, namely Chinese shipping stock sector index (SI), Panamax freight rate (PF), WTI oil futures (OF), China Yuan exchange rate (ER).

In this study, we use daily closing prices of the shipping sector stock index as measured by 20 shipping companies listed in the Shanghai Stock Exchange, the oil futures as measured by the WTI (West Texas Intermediate), the freight price as measured by average chartering of 4 routes of Panamax in China and the exchange rate as measured by the RMB/USD nominal closing exchange rate, starting from 1_{st} January 2007 to 30_{th} March 2018. The missing values were filled by the previous day data. Before using these data for analyzing, we transform each price data series into the logarithmic returns, $\ln \frac{p_t}{p_{t-1}}$.

3.5 Research Methodology

3.5.1 The Index Return

In order to ensure that the data is stationary, we covert the data into logarithmic returns which the process can be expressed as:

$$R_t = \ln \frac{p_t}{p_{t-1}}, \tag{3.7}$$

where R_t representing the log-return of the data. P_t , P_{t-1} is the daily return of the data at time t and $t-1$, respectively.

3.5.2 Unit Root Test

3.5.2.1 Augmented Dickey-Fuller (ADF) Test

The Augmented Dickey-Fuller (ADF) unit root test is an augmented

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version of the Dickey-Fuller (DF) test, is used to accommodate some form of serial correlation. Three versions of ADF can be examined the stationary property of a series.

(1)Test for a unit root

$$\Delta y_t = \varphi^* y_{t-i} + \sum_{i=1}^{p-1} \varphi^* y_{t-i} + \mu_t , \tag{3.8}$$

(2)Test for a unit root with a constant

$$\Delta y_t = \beta_0 + \varphi^* y_{t-i} + \sum_{i=1}^{p-1} \varphi^* y_{t-i} + \mu_t , \tag{3.9}$$

(3)Test for a unit root with a constant and deterministic time trend

$$\Delta y_t = \beta_0 + \varphi^* y_{t-i} + \sum_{i=1}^{p-1} \varphi^* y_{t-i} + \mu_t , \tag{3.10}$$

where y_t = the value of a variable at time period t

$\Delta y_t = y_t - y_{t-1}$

β_0 = a constant term

t = a linear time trend

μ_t = an error term

In order to test the presence of unit root, it's needed to calculate T statistic $\pi = \frac{\varphi^*}{\sqrt{\mathrm{var}(\varphi^*)}}$ and then compare its to the corresponding critical value at different significant level (Xu 2010).

3.5.2.2 Phillips-Perron Test (PP Test)

In statistics, the Phillips-Perron Test is a unit root test.

$$DY_t = \alpha + \beta_t Y_{t-1} + \varepsilon_t , \tag{3.11}$$

The PP-test makes a correction to the t-statistic of γ coefficient from AR(1) regression to account for the serial correlation in equation (3.11). The correction is nonparametric since use an estimate of the spectrum of equation (3.11) at frequency zero that is robust to heteroskedasticity and autocorrelation of unknown form.

$$\gamma_j = (1/T)\sum_{t=j+1}^{T} \varepsilon_t^* \varepsilon_{t-j}^* , \tag{3.12}$$

$$w^2 = \gamma_0 + 2\sum_{j=1}^{q} [1 - j/(q+1)]\gamma_j , \tag{3.13}$$

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where,

w^2 = Newey-west heteroskedasticity autocorrelation consistent estimate

γ_j = coefficient from AR(1) in equation (3.11)

$\varepsilon_t^* \varepsilon_{t-j}^*$ = error term received from equation (3.11)

q = floor $(4(T/100)^{2/9})$, [q is the truncation lag]

3.5.2.3 The KPSS-Test

The KPSS statistic is based on the residuals from the OLS regression of y_t on the exogenous variables x_t (see equation (3.14) and x_t is a random walk: $x_t = x_{t-1} + \varepsilon_t$.

$$y_t = x_t + \varepsilon_t, \tag{3.14}$$

$x_t : x_t = \alpha_0 + b_0 t + \varepsilon_t$ (Intercept and trend)

$x_t : x_t = \alpha_0 + \varepsilon_t$ (Intercept)

ε_t : is a stationary random error

y_t : is data test stationary or non-stationary

Regress y_t on x_t or regress y_t on a constant and a trend then obtain the residual ε_t as well as take this residual to calculate in the KPSS statistic.

$$KPSS = T^{-2} SS_t^2 / (s^2(L)), \tag{3.15}$$

where T is the simple size

$$S_t^2 = \sum_{i=1}^{t} \varepsilon_t , \tag{3.16}$$

$$s^2(L) = T^{-1} \sum_{t=1}^{T} \varepsilon_t^2 + 2T^{-1} \sum_{S=L}^{L} w(s,L) \sum_{t=s+1}^{T} \varepsilon_t \varepsilon_{t-s}, \tag{3.17}$$

where $w(s,L)$ is an optional function corresponding to the choice of a spectral window, $w(s,L) = 1 - s/(L+1)$ in estimation (see Newey and West 1987; Kwiatkowski et al., 1992)

$L =$ the number of truncation (lags) is chosen

The KPSS test method test for unit root has the hypothesis to be tested

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are H_0 (null hypothesis) and H_1.

$$H_0 : s^2 = 0(y_t \sim 1(0)) \text{ time series is stationary}$$

$$H_1 : s^2 > 0(y_t \sim 1(1)) \text{ time series is non-stationary}$$

If KPSS-statistics > Quantities of distribution of KPSS statistics table as reject H_0 or rejected null hypothesis and accepted H_1 then conclusion that y_t is non-stationary.

If KPSS-statistics < Quantities of distribution of KPSS statistics table as reject H_0 or rejected H_1 then conclusion that y_t is stationary.

Table 3.1: Unit Root Test

Unit Root Test	**ADF**	**PP**	**KPSS**
Null Hypothesis: H_0	Time series is non-stationary	Time series is non-stationary	Time series is stationary
Alternative Hypothesis: H_0	Time series is stationary	Time series is stationary	Time series is non-stationary
Statistic test	t-Statistic	t-Statistic	t-Statistic
Prob.< 0.1	0.00-0.10	0.00-0.10	0.00-0.10

Source: By author

3.5.3 Generalized Autoregressive Conditional Heteroskedasticity

In this section, we describe the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model which was proposed by (Bollerslev, 1986). Then, we combine the autoregressive (AR) and moving average (MA) terms with skewed student-*t* distribution to find the marginal distributions. This model can capture the important characteristic of financial volatility.

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The ARMA(p,q)-GARCH(1,1) model can be expressed as the following:

$$R_t = \varphi_0 + \sum_{i=1}^{p} \varphi_i R_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t , \tag{3.18}$$

$$\varepsilon_t = h_t^{1/2} z_t , \tag{3.19}$$

$$h_t = \omega_0 + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \tag{3.20}$$

where the ARMA (p,q) process is presented by equation (3.18), where y_{t-i} is an autoregressive term of y_t and ε_t is an error term, it defines this residual as the production between the conditional variance h_t and random variable z_t in equation (3.19).

Equation (3.20) displays the GARCH (1,1) process, where $\omega_0, \alpha, \beta > 0$ and $\alpha + \beta < 1$ are sufficient to ensure that the conditional variance ht is greater than zero. The ARCH term is represented by $\alpha\varepsilon_{t-1}^2$ .The α refers to the short-run persistence of shocks, The GARCH term is represented by βh_{t-1}. The β refers to the contribution of shocks to the long-run persistence $(\alpha + \beta)$.

In equation (3.19), we assume that z_t follows the skewed student- t (SkT) distribution, where v stands for the freedom and λ stands for the skewness parameter. The formula of the skewed student-t distribution is expressed as follows:

$$g(zv, \lambda) = \begin{cases} qc\left(1 + \dfrac{1}{v-2}\left(\dfrac{qz+d}{1-\lambda}\right)^2\right)^{-(v+1)/2} & , z \le -d/q \\ \\ qc\left(1 + \dfrac{1}{v-2}\left(\dfrac{qz+d}{1+\lambda}\right)^2\right)^{-(v+1)/2} & , z \ge -d/q \end{cases}, \tag{3.21}$$

where the constant d, q and c are given as follows:

$$d = 4\lambda c\left(\frac{v-2}{v-1}\right), \quad q^2 = 1 + 3\lambda^2 - d^2, \quad c = \frac{\Gamma\left(\dfrac{v+1}{2}\right)}{\sqrt{\pi(v-2)}\,\Gamma\left(\dfrac{v}{2}\right)}, \tag{3.22}$$

The λ is parameter asymmetry which is restricted within (-1,1).

3.5.4 The Ljung-Box Test

In order to identify of lags in autoregression, usually use Box-Pierce (1970) Portmanteau statistic.

The joint statistic hypothesis $\hat{\rho}_1 = \hat{\rho}_2 = ... = \hat{\rho}_k$.

$$Q(s) = T\sum_{k=1}^{s} \hat{\rho}_k^2, \tag{3.23}$$

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Assuming $Y_t \sim WN(0,\sigma^2)$ it is straight forward to show that:

$$Q(s) \xrightarrow{d} \chi^2(s), \tag{3.24}$$

Reject $\hat{\rho}_1 = \hat{\rho}_2 = ... = \hat{\rho}_k$ if $Q(s) \geq \chi^2_{0.95}(s)$

Ljung and Box (1978) purposed modifies version of Box-Pierce test as:

$$Q^*(s) = T(T+2)\sum_{k=1}^{s} \frac{\hat{\rho}_k^2}{(T-k)}, \tag{3.25}$$

where, Q^* follow $\chi^2(s)$ or $Q^*(s) \rightarrow \chi^2(s)$.

Ljung-Box is a Portmanteau test and an adjustment to the Box-Pierce chi-square statistic. Ljung-Box is also used to evaluate hypotheses after fitting a time series model (e.g. ARMA model) to ensure that the residuals are independent of each other.

3.5.5 KS Test (Kolmogorov-Smirnov Test)

The Kolmogorov-Smirnov test (KS test) is based on cumulative distribution function. Two-sample KS test is one of the most useful and conventional non-parametric methods for comparing two samples because it is sensitive to the difference of the position and shape parameters of the empirical distribution function of two samples.

We could use the KS test to examine the goodness of fit of the marginal distribution of return series. The KS test is defined by:

H_0 : The data follow a specified distribution.

H_1 : The data do not follow the specified distribution.

Test statistic is:

$$D = \max_{1 \leq i \leq N}(F(Y_i) - \frac{i-1}{N}, \frac{i}{N} - F(Y_i)), \tag{3.26}$$

where F is the theoretical cumulative distribution of the distribution being tested which must be a continuous distribution, and it must be fully specified (i.e., the location, scale, and shape parameters cannot be estimated from the data). Given N order data points $Y_1, Y_2, ..., Y_N$, the empirical distribution function is $E_N = n(i)/N$, where *n(i)* is the number of points less than Y_i and the Y_i are order from smallest to largest value. This is a step

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function that increases by $1/N$ at the value of each ordered data point.

3.5.6 Information Criteria

The two most widely used criteria are the Akaike Information Criterion (AIC) and the Bayesian Criterion (BIC). They are a measure of the goodness of fit in statistical models as:

$$AIC(k) = n \log \hat{\sigma}^2_{ML} + 2k, \tag{3.27}$$

$$BIC(k) = n \log \hat{\sigma}^2_{ML} + k \log n, \tag{3.28}$$

where k is number of parameters $(p+q)$.

The selection criteria:

$$\min_{p \le P, q \le Q} AIC(p,q)$$

$$\min_{p \le P, q \le Q} BIC(p,q)$$

3.5.7 The Copula Model

Copulas were invented in 1959 and are popular in high-dimensional statistical applications because they allow the modeling of random vectors to be easily model and estimated by separately estimating boundaries and dependencies. There are many parameters available for the copula series, which typically have parameters that control dependency intensity. The modeling of random multivariate events is a central problem in variables scientific domains and the construction of multivariate distribution able to properly model the variables at play is challenging. A useful tool to deal with this problem is the concept of the copula.

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Let H be an n-dimensional distribution function with marginals $F_1,...,F_n$, and $X = (X_{1,...,}X_n)'$ be a random vector with the distribution function. The exists a unique function C is given by:

$$H(X_1,...,X_n) = C(F_1(X_1),...,F_n(X_n)),(X_1,...,X_n) \in \tag{3.29}$$

where C is a copula and $F_1,...,F_n$ are distribution functions, above function $H(x_1,...,x_n)$ in equation (3.29) is a joint distribution function with marginal distribution $F_1,...,F_n$. C can be interpreted as the distribution function of an n-dimensional random variable on

$[0,1]^n$ with uniform margins.

$$C(u_1,...,u_n) = H(F_1^{-1}(u_1),...,F_n^{-1}(u_n)), \tag{3.30}$$

In this study, we apply both of Elliptical copulas and Archimedean copulas. Elliptical copula families consist of Gaussian and Student-*t* copula. Archimedean copula families compose Clayton, Gumbel, Frank, Joe copula.

The six copula families are chosen to measure the dependence in this study.

3.5.7.1 Elliptical Copulas

(1) Multivariate Gaussian copula

Multivariate Gaussian copula is one of the most widely used econometric methods in finance and it's related to the multivariate normal distribution. Elliptical copulas are derived from the elliptical distribution by applying Sklar's theorem. The most common are the Gaussian and the Student-*t* copulas, which are symmetric (Marius and Hasim, 2018).

The *n*-dimensional Gaussian copula has the following expression:

$$C(u_1,...,u_n) = \Phi_n^{\sum^n}(\Phi_1^{-1}(u_1),...,\Phi_1^{-1}(u_n)), \tag{3.31}$$

where $\Phi_n^{\sum^n}$ denotes *n*-dimension standard normal cumulative distribution and $\sum n$ the corresponding correlation matrix.

The density can be written as:

$$c(u_1,...,u_n) = \frac{1}{\sqrt{\det \sum_n}} \exp\left(-\frac{1}{2} \begin{pmatrix} \Phi_1^{-1}(u_1) \\ ... \\ \Phi_1^{-1}(u_n) \end{pmatrix}^T . \left(\sum\nolimits_n^{-1} - \mathrm{I}\right) . \begin{pmatrix} \Phi_1^{-1}(u_1) \\ ... \\ \Phi_1^{-1}(u_n) \end{pmatrix} \right), \tag{3.32}$$

where I denotes $n \times n$ identity matrix. The Gaussian copula has zero tail dependence.

(2) Multivariate Student-*t* copula

Multivariate Student-*t* copula can be thought of as representing the dependence structure implicit in a multivariate *t* distribution. It is a model that has received much recent attention, particularly in the context of modeling multivariate

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financial volatility.

The n-dimensional student-t copula is defined as:

$$C(u_1,...,u_n) = \int_{-\infty}^{t_v^{-1}(u_1)} ... \int_{-\infty}^{t_v^{-1}(u_n)} f_{t_1(v)}(x)dx, \tag{3.33}$$

where $f_{t_{1(v)}}(x)$ denotes n-dimensional student-t density function with degree of freedom v and t_v^{-1} denotes the quantile function of a standard univariate student-t distribution with a degree of freedom v . The t-copula has symmetric non-zero tail dependence.The density can be written as:

$$c(u_{1,...,}u_n) = |\rho|^{-\frac{1}{2}} \frac{\Gamma\left(\frac{v+d}{2}\right)}{\Gamma\left(\frac{v}{2}\right)} \left(\frac{\Gamma\left(\frac{v}{2}\right)}{\Gamma\left(\frac{v+1}{2}\right)} \right)^d \frac{\left(1+\frac{1}{v}\varsigma'\rho^{-1}\varsigma\right)^{-\frac{v+d}{2}}}{\prod_{j=1}^{n}\left(1+\frac{\varsigma_j^2}{v}\right)^{-\frac{v+1}{2}}}, \tag{3.34}$$

where ρ is a matrix with $diag(\rho) = (1,1,...,1)^{tr}$,$\varsigma = (\Phi_1^{-1}(u_1),...,\Phi_1^{-1}(u_n))'$.

3.5.7.2 Archimedean Copulas

Archimedean copulas allow for a large variety of different dependence structures and also have explicit expressions. Comparing with elliptical copulas, Archimedean copulas are not derived from multivariate distributions using Sklar's theorem.

An Archimedean generator is a continuous, decreasing function ψ: $[0,\infty] \to [0,1]$ which satisfity $\psi(0) = 1$, $\psi(\infty) = \lim_{t\to\infty}\psi(t) = 0$ and strictly decreasing on $[0, \inf\{t : \psi(t) = 0\}]$ An n-dimensional copula C is called Archimedean if it has the following representation:

$$C(u_1,...,u_n) = \psi(\psi^{-1}(u_1) + ... + \psi^{-1}(u_n)),\ u_i \in [0,1],\ i \in \{1,...,n\}, \tag{3.35}$$

where some generator ψ with inverse $\psi^{-1} : [0,\infty] \to [0,1]$,where $\psi^{-1}(0) = \inf\{t : \psi(t) = 0\}$

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Table 3.2: One-parameter Archimedean Generators ψ.

Family	**Parameter**	**Generator** $\psi(t)$	**Inverse Generator** $\psi(t)^{-1}$
Clayton	$\theta \in (0,\infty)$	$(1+t)^{-1/\theta}$	$t^{-\theta}-1$
Frank	$\theta \in (0,\infty)$	$-\frac{\log(1-(1-\exp(-\theta))\exp(-t))}{\theta}$	$-\log(\frac{\exp(-\theta t)-1}{\exp(-\theta)-1})$
Gumbel	$\theta \in [1,\infty)$	$\exp(-t^{1/\theta})$	$(-\log(t))^{\theta}$
Joe	$\theta \in [1,\infty)$	$1-(1-\exp(-t))^{1/\theta}$	$-\log(1-(1-t)^{\theta})$

Source: Numerical approximations and Goodness-of-fit of Copulas.

An Archimedean copula C is defined by the generator ψ if and only if ψ is n-monotone. Several well-known parametric generator families referred to as Archimedean families are in Table 3.2.

Table 3.3 summarizes properties concerning Kendall's tau and the tail-dependence coefficients. We see that Clayton copula only has lower tail dependence while Gumbel copula and Joe copula have only upper tail dependence. For Frank copula, there is no tail dependence. Such properties are often used to select suitable copula families for estimation. In table 3.3, $D_1(\theta)=\int_0^{\theta} t/(\exp(t)-1)dt/\theta$ denotes the Debye function of order one.

Table 3.3: Kendall's tau and tail-dependence coefficients.

Family	τ	λ_L	λ_U
Clayton	$\theta/(\theta+2)$	$2^{-1/\theta}$	0
Frank	$1+4(D_1(\theta)-1)/\theta$	0	0
Gumbel	$(\theta-1)/\theta$	0	$2-2^{-1/\theta}$
Joe	$1-4\sum_{k=1}^{\infty} 1/(k(\theta k+2)(\theta(k-1)+2))$	0	$2-2^{-1/\theta}$

Source: Numerical approximations and Goodness-of-fit of Copulas

(1) Multivariate Clayton copula

The Clayton copula provides strong lower tail dependence and has the following density:

$$c_\theta(u)=\prod_{m=0}^{n-1}(\theta m+1)(\prod_{j=1}^{n}u_j)^{-(1+\theta)}(1+t_\theta(u))^{-(n+1/\theta)}, \qquad (3.36)$$

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where $\theta>0$ to satisfies the decreasing means, which is able to reflect the lower tail dependence. Clayton copula can be rotated and applied to capture negative dependence or reflect strong upper tail dependence, The corresponding Kendall's tau measure is simply given by $\tau_{CL} = \theta/\theta + 2$. However, the association between the copula parameter and the Spearman's rho is very complicated, and the lower tail dependence can be also simply calculated by $\lambda_L = 2^{-1/\theta}$.

(2) Multivariate Frank copula

Although the Archimedean class of copulas is popular in empirical applications, the Frank copula in Archimedean copulas is only one who can gain both lower and upper bounds, thus allowing positive and negative dependence.The density is given by:

$$c_\theta(u) = \left(\frac{\theta}{1-\exp(-\theta)}\right)^{n-1} Li_{-(n-1)}(h_\theta^F(u)) \frac{\exp(-\theta\sum_{j=1}^{n} u_j)}{h_\theta^F(u)}, \tag{3.37}$$

where $h_\theta^F(u) = (1-\exp(-\theta))^{1-n} \prod_{j=1}^{n} (1-\exp(-\theta u_j))$. The above function is the only Archimedean copula that satisfies the functional equation $C(\mu,\eta) = \hat{C}(\mu,\eta)$. Then the marginal distribution becomes radially symmetric.

(3) Multivariate Gumbel copula

The Gumbel copula is non-symmetric and exhibits strong upper tail dependence and and has the following density:

$$c_\theta(u) = \theta^n C_\theta(u) \frac{\prod_{j=1}^{n}(-\log u_j)^{\theta-1}}{t_\theta(u)\prod_{j=1}^{n} u_j} P_{n\alpha}^G(t_\theta(u)^{1/\theta}), \tag{3.38}$$

where $P_{n,\alpha}^G(x) = \sum_{m=1}^{n} a_{nm}^G(\alpha)x^m$, $a_{nm}^G(\alpha) = (-1)^{n-m}\sum_{n=m}^{n} \alpha^j s(n,j)S(m,j)$ and s denotes the Stirling numbers of the first kind and S the Stirling numbers of the second kind.

(4) Multivariate Joe copula

The Joe copula has a higher dependence in the upper tail than in the lower tail, where it is zero. It has the following density:

$$c_\theta(u) = \theta^{n-1} \frac{\prod_{j=1}^{n}(1-u_j)^{\theta-1}}{h_\theta^J(u)} (1-h_\theta^J(u))^\alpha P_{n\alpha}^J\left(\frac{h_\theta^J(u)}{1-h_\theta^J(u)}\right), \tag{3.39}$$

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where $h_{\theta}^{J}(u)=\prod_{j=1}^{n}(1-(1-u_{j})^{\theta})$, $P_{n,\alpha}^{J}(x)=\sum_{m=0}^{n-1}a_{nm}^{J}(\alpha)x^{m}$, $a_{nm}^{J}(\alpha)=S(n,m+1)(m-\alpha)_{m,}$ and $(m-\alpha)m=\dfrac{\Gamma(m+1-\alpha)}{\Gamma(1-\alpha)}$ denotes the falling factorial.

3.5.8 VAR Model

Vector autoregressions (VARs) were introduced into empirical economics by C.Sims (1980), who demonstrated that VARs provide a flexible and tractable framework for analyzing economic time series.

We set up a covariance stationary *N*-variable VAR(P), it can be written as follows:

$$H_{t}=\psi_{0}+\sum_{i=1}^{p}\psi_{i}H_{t-i}+\varepsilon_{t}, \tag{3.40}$$

where $H_{t}=\{h_{1t},...,h_{Nt}\}$ denote an $(N\times 1)$ vector of conditional volatilities obtained form GARCH process. ψ_{0} is the deterministic components of the VAR system, the ψ_{i} is $(N\times N)$ coefficient matrices. The $\varepsilon\sim(0,\,\Sigma)$ is a vector of independently and identically distributed disturbances. In our study, we test the volatility spillovers using a four-variables VAR model across different markets.

3.5.9 Impulse Response Function

The impulse response function analysis explains how studies variables respond in standard deviation when there is a shock. When a shock occurs temporary, the IRF considers how long studied variables adjust their values to the mean value.

Then, we can investigate the impulse response function through the moving average specification $R_{t}=\sum_{i=0}^{\infty}A_{i}\varepsilon_{t-i}$, where A_{i} is the $(N\times N)$ coefficient matrices follow $A_{i}=\Psi_{1}A_{i-1}+\Psi_{2}A_{i-2}+...+\Psi_{p}A_{i-p}$, with A_{0} the $(N\times N)$ identity matrix and $A_{i}=0$ for *i<0*.

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CHAPTER 4

Empirical Analysis

In this chapter, the relationship, and dependence structure among the shipping sector stock index, WTI oil futures price, the Panamax freight price, and the RMB/USD nominal closing exchange rate will be discussed according to the empirical results.

4.1 Current Situation

4.1.1 Shipping Industry

Ten years have passed since the outbreak of the economic crisis in 2008. During this decade, the shipping industry fell from the peak to the bottom, the freight rate continued to be low, the market sentiment has been relatively pessimistic. Although there has been some improvement in the period, it has not yet returned to prosperity due to the huge surplus of the world economy and capacity.

Source: ZGSYB.com

Figure 4.1: Baltic Dry Index monthly chart.

From 2008 to now, the shipping market experienced the highest value of BDI (Baltic Dry Index) is 11,793 points, and then began a sharp decline in July 2008, and remained depressed, even falling below 300 points in 2016. This phenomenon is in line with the performance of the recession period in the traditional cycle. On the one hand, the worldwide financial crisis in 2008 led to a downturn in international trade the volume and reduced demand of the shipping industry. On the other hand, it accumulated a lot of capacity during the peak shipping season. Orders for new ships reached 975 million deadweight tons in 2008, making the supply far greater than the demand. These two aspects cause the shipping market supply and demand to be seriously unbalanced, the shipping price to drop substantially.

From 2010 to 2015, too many investors entered the shipping market and ordered a large number of ships, making the imbalance between supply and demand in the shipping market more and more serious. Under the participation of too many human factors, the self-adjustment ability of the shipping market was not well reflected. In 2016, the problems caused by excess capacity finally broke out and the BDI reached an all-time low below 300. There was an upturn in 2017, but the world economy and a massive overhang of capacity failed to revive the boom.

4.1.2 WTI Oil Futures Market

As an important factor that affects the cost and profit of shipping, oil has played an important part in most of the economies in the world as well as in China. Its demand and supply will contribute a direct and potential impact on the financial markets (Sukcharoen, 2014). In fact, the oil futures price continues to fluctuate along this decade. It falls sharply in December 2008 and rises again until a decline in February 2016, then gradually rise. Consequently, the link between oil and oil-related industries are strengthened because of this volatility (Apergis, 2009).

China's first serious try to set up an Asian oil price benchmark was organized by the Shanghai International Energy Exchange (INE) in late March to a strong response. It has increased its share of the spot market by about 6 percent compared with international Brent LCOc1 and U.S. West Texas Intermediate (WTI) CLc1, also taken from the two benchmarks (Business News, 2018).

Global oil futures volumes have more than doubled since 2013, but exchange data suggest WTI and Brent activity will fall in 2017 for the first time since 2013. WTI and Brent volumes slipped to 207.2 million lots of 1,000 barrels each for this year by Dec. 10, down from 220.17 million lots in 2017.

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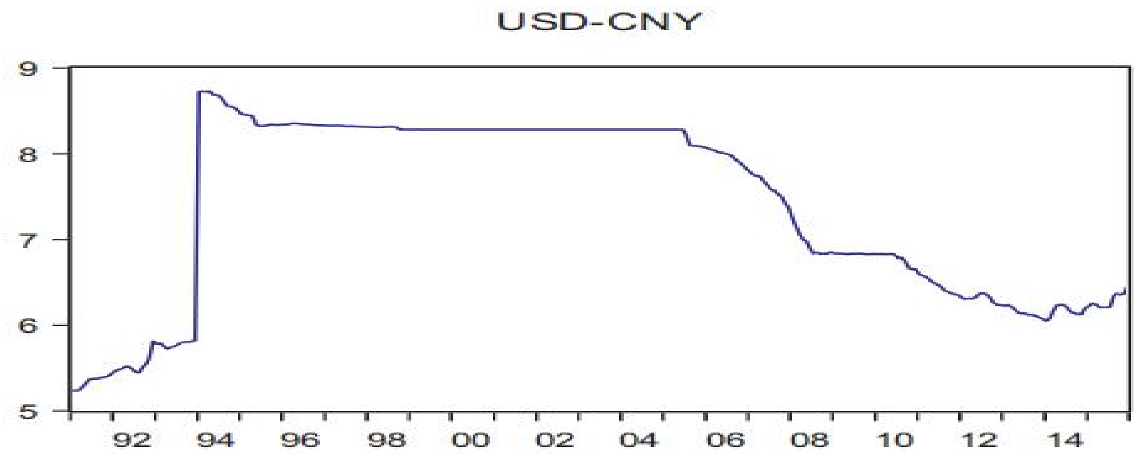
4.1.3 RMB/US Exchange Rate

In terms of exchange rates, many goods are denominated in dollars, measured by the U.S. dollar terms relative to their most important trading partners. The USD-CNY exchange rate paused around 8.27 yuan per USD until June 2005, when China managed a new administered float and switched the peg from the U.S. dollar to a basket of currencies.



Source: Bloomberg.

Figure 4.2: Time-series plots of the exchange rate of the RMB per U.S. dollar.

In January 1994, China abolished the dual-track exchange rate system and combined the official exchange rate with the foreign exchange adjustment price, devaluing the RMB exchange rate from 5.8 to 8.6 in one time, or about 33%. In July 2005, China formally announced the implementation of the floating exchange rate system, and the RMB exchange rate system was changed from the original peg to the U.S. dollar to "a managed floating exchange rate system based on market supply and demand and adjusted with reference to a basket of currencies". On December 1, 2015, the International Monetary Fund announced that the RMB will join the Special Drawing Rights (SDR) currency basket on October 1, 2016, with a proportion of 10.92%.

4.2 Descriptive Statistics

This paper employs the multivariate copula model and the VAR model to estimate the dependence and volatility spillover among shipping sector stock index which is measured by SSE (Shanghai Stock Exchange) sector indices, Panamax freight price as measured by average chartering of 4 routes, the RMB/USD nominal closing exchange rate and WTI oil futures price. In order to ensure that the data is stationary, we covert

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the data into logarithmic returns.

Descriptive statistics are used to describe the basic features of the data in a study. They provide simple summaries about the sample and the measures. Together with simple graphics analysis, they form the basis of virtually every quantitative analysis of data. In order to use VAR estimation all the time-series data have to be stationary at level, we need to check the stationary condition of the data set by using the Augmented Dickey- Fuller unit root test, and the Phillips-Perron unit root tests, and the Kwiatkowski stationary test.

Table 4.1: Summary statistics

	Shipping Sector	**Freight Price**	**Exchange Rate**	**Oil Futures**
Minimum	-0.1072	-0.6001	-0.0119	-0.1307
Maximum	0.0950	0.5386	0.01839	0.1641
Mean	0.0000	-0.0004	-0.0001	0.00003
Std.Dev.	0.0241	0.0392	0.0014	0.0238
Skewness	-0.3331	-0.9458	0.5628	0.1428
Kurtosis	6.2207	78.1666	20.4130	7.9139
Jarque-Bera	1320.1100***	689972.3010*	37158.9401***	2956.7700***
ADF	-50.3368***	-20.7384***	-30.3788***	-56.8968***
PP	-50.5992***	-51.3035***	-52.1404***	-56.9302***
KPSS	0.1122	0.0545	0.8334	0.1010

Notes: Std.Dev. is the standard deviations. ADF means Augmented Dickey-Fuller test. Significant codes: 0*** 0.01 ** 0.05 * 0.1.

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Table 4.1 presents the descriptive statistics of four data series (China's shipping sector stock index, oil futures price, shipping freight price and RMB/USD nominal closing exchange rate). In terms of mean value, the return rate of shipping freight price and exchange rate are negative. Indicating that in the post-financial crisis era, the index generally presents a downward trend and the return rate declines. The maximum, minimum and standard deviation (Std. dev. in Table 4.1) indicate the presence of outliers.

The skewness statistic of the shipping sector and freight price are negative, thereby indicating that the shipping sector and freight price returns are skewed to the left. With respect to the kurtosis statistics, the value of both price returns is greater than 3 which indicates a fat-tailed distribution. Similarly, the Jarque-Bera statistics are large and significant which means that our data may not follow the normal distribution, thereby implying that the assumption of skewed-*t* is more appropriate in our study. The sample skewness and kurtosis indicate the non-normal distribution of the returns, which is also supported by the Jarque-Bera test. Furthermore, the results of Augmented Dickey-Fuller (ADF) , the Phillips-Perron (PP) and the Kwiatkowski-Phillips Schmidt-Shin (KPSS) unit root tests show that four price returns are stationary at level 1%.

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4.3 Dependency Analysis

4.3.1Results of ARMA-GARCH Model

Table 4.2: Estimates of the marginal distribution models

	Shipping Sector	**Freight Price**	**Exchange Rate**	**Oil Futures**
Mean equation				
ϕ_0	0.0004 (0.0005)	-0.0006 (0.0010)	-0.00002 (0.00001)	0.0003 (0.0003)
ϕ_1	0.9943*** (0.0024)	0.5803*** (0.0394)	0.2146*** (0.0490)	-1.9854*** (0.0010)
ϕ_2			-0.1044. (0.0869)	-1.0286*** (0.0011)
ϕ_3			0.2741*** (0.0709)	-0.0210*** (0.0006)
ϕ_4			0.5126*** (0.0197)	
ϕ_5			0.0801*** (0.0168)	
θ_1	-0.9867*** (0.0001)	0.3733*** (0.0425)	-0.2484*** (0.0469)	1.9558*** (0.0000)
θ_2		0.2637*** (0.0379)	0.0721. (0.0878)	0.9780*** (0.0001)
θ_3		0.1547*** (0.0301)	-0.2397*** (0.0735)	
θ_4		0.1054*** (0.0196)	-0.5305*** (0.0129)	
θ_5		0.0398*** (0.0092)		
Variance equation				
Cst(v)	0.0000*** (0.0000)	0.0001*** (0.0000)	0.0000 (0.0000)	0.0000 ** (0.0000)
ARCH (Alphal)	0.1104*** (0.0130)	0.8388*** (0.0893)	0.0901*** (0.0194)	0.0586*** (0.0038)
GARCH (Betal)	0.8886*** (0.0107)	0.1602*** (0.0375)	0.8964*** (0.0221)	0.9384*** (0.0029)
Asymmetry	0.9398*** (0.0201)	1.0659*** (0.0243)	0.9693*** (0.0183)	0.9445 *** (0.0237)
Tail	4.1284 *** (0.347880)	2.7840*** (0.1085)	4.2871*** (0.2198)	7.9701*** (1.1154)
LogLik	7365.3020	8443.6420	16223.1700	7380.5880
AIC	-5.0238	-5.7574	-11.0670	-5.0322

Note: The standard error is in parenthesis. Significant codes: 0*** 0.01 ** 0.05 * 0.1.

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In this paper, the ARMA (p,q)-GARCH (1,1) model is applied to estimate the marginals for each series, and suppose that all marginals follow skewed student-*t* distributions. The model estimation results are showed in Table 4.2. The optimal lag for ARMA(p,q) is selected by using the AIC (Akaike information criterion) and find that the returns on Shipping Stock, Freight Price, USD_CNY and Oil Futures satisfy ARMA (1,1), ARMA (1,5), ARMA (5,4) and ARMA (3,2) with GARCH(1,1) , respectively. The parameter ARCH and GARCH are significant, and the summation between them is close to one, demonstrating that the conditional volatility is very persistent over time.

On comparing the results, we can see that the Freight Price exhibits comparatively higher α values than the other three markets in ARMA(p,q)-GARCH(1,1) model. This may imply that the shipping freight market shows less market efficiency than the other markets as the effects of the shocks take a longer time to dissipate. The β parameters capture long term influences on volatility. What is interesting to note that three markets exhibit very similar β values expect shipping freight market. This shows that long term effects have similar influences on market volatility. We also observe that values of asymmetry are both significant, indicating the skewness behavior of our marginals.

Table 4.3: Estimated results for the KS test and Box-Ljung Test (Q-Test)

	Shipping Stock	**Freight Price**	**USD_CNY**	**Oil Futures**
Q(1)	0.3680	0.9712	0.9869	0.0232
Q(5)	0.2859	0.9998	1.0000	0.1086
Q(9)	0.1361	0.9990	1.0000	0.2596
KS	0.0535	0.2776	0.0573	0.4089

Notes: *Q(q)* is Ljung-Box p-value for serial correlation order q. The KS means Kolmogorov-Smirnov test for uniformity.

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To avoid copula model missimplification, the adequacy of the estimated ARMA(p,q)-GARCH(1,1) model is also tested through the auto-correlation Ljung-Box test. We provide several order auto-correlation tests for possible misspecification consisting of Ljung-Box *Q(1)*, *Q(5)*, and *Q(9)*. Table 4.3 reports the results which show that all standardized residual series are not rejected auto-correlation, verifying the independently distributed. After filtering the data using ARMA(p,q)-GARCH(1,1) models, the obtained standardized residuals are transformed to uniforms using the cumulative skewed student-*t* distributions. The uniform series will be used as input for the multivariate copula. Prior to estimating the copula model, the transformed standardized residuals must be uniformly distributed. Consequently, we perform the KS test to verify whether marginals are uniform [0,1]. The results are also showed in Table 4.3 and we observe that four marginal distributions are uniform [0,1].

4.3.2 Estimate Results of Copula Models

Table 4.4: Model selection

Copulas	**Loglik**	**AIC**	**BIC**
Student-*t*	44.9117	-75.8233	-33.9464
Gaussian	44.3364	**-76.6729**	**-40.7784**
Clayton	-74.8606	151.7213	157.5857
Frank	-6.6143	15.2287	21.0931
Gumbel	-164.9503	331.9006	337.7650
Joe	-92.5619	187.1238	192.9883

Notes: Loglik means log-likelihood. The lowest value of AIC (in bold) suggests the best copula fit.

Prior to analyzing our results, we compare six copula models as mentioned in Chapter 3. Table 4.4 shows the values of the log-likelihood, the AIC, and the BIC. From the AIC and BIC perspective, and the Gaussian copula displays better explanatory ability than the other copulas as the AIC and BIC values of this copula are -76.6729 and -40.7784, respectively, which is the minimum of all copulas.

Table 4.5: Theoretical Kendall tau based Gaussian copula

	Shipping Stock	**Freight Price**	**USD_CNY**	**Oil Futures**
Shipping	1.0000	0.0649	-0.1034	0.0736
Freight Price	0.0649	1.0000	-0.0391	0.0112
USD_CNY	-0.1034	-0.0391	1.0000	-0.0756
Oil Futures	0.0736	0.0112	-0.0756	1.0000

Table 4.5 displays the dependence analysis of the Gaussian copula. The dependence correlation coefficients from Table 4.5 shows that four market volatilities display a weak degree of dependence. We find that the dependence between the shipping sector stock price and currency market is the strongest while the dependence between the freight market and oil futures market is the weakest. The copula correlation coefficient between the shipping sector stock price and currency market is -0.1034. This

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implies that these two markets are related in the opposite direction and the shipping sector movements are affected by the currency market. The relationship between the shipping sector and freight market; and the shipping sector and oil futures market are found to have dependence equal 0.0649 and 0.0736, respectively. It means that these two market pairs are slightly related in the same direction. Considering the relationship between freight and currency market; and oil futures and currency market, they has a low negative coefficient -0.0391 and -0.0756, respectively. These imply that the freight and oil futures market have a negative influence on the dependence of the currency market.

The low correlations among these markets can be illustrated by the price control policy: oil futures prices are related to international crude oil prices which are less affected by China's economy. And China's securities market is an emerging market, the degree of market maturity and linkage with the outside is still very low, the internationalization of the securities market still has a long way to go. Another variable exchange rate is also regulated by the government, thus having less links with the international market.

4.4 Spillover Effect Analysis

We then examine the daily volatilities across the shipping sector stock price, shipping freight market, currency market, and oil futures market. The results from the Augmented Dickey-Fuller test reveal that all the series are stationary in the form of first differences. Then we use a VAR (1) model, where the lag length of one is chosen by the AIC. Thus, we regress the daily volatility in each market on one lag of itself, as well as one lag of volatility in each of the three other markets.

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4.4.1 Estimate Results of VAR Model

Table 4.6: Results of VAR model

	Shipping Stock	Freight Price	USD_CNY	Oil Futures
Constant	-0.0036 (0.0181) [-0.2030]	0.0231 (0.0320) [0.7210]	0.0069 (0.0485) [0.1430]	-0.0158 (0.0186) [-0.8510]
Shipping Stock t-1	0.0324. (0.0185) [1.7520]	0.0844* (0.0330) [2.5600]	0.0111 (0.0499) [0.2240]	0.0199 (0.0191) [1.0430]
Freight t-1	0.0070 (0.0104) [0.6780]	-0.0506** (0.0184) [-2.7410]	0.0259 (0.0279) [0.9270]	0.0011 (0.0107) [0.0107]
USD_CNY t-1	0.0057 (0.0069) [0.8290]	-0.0010 (0.0123) [-0.0800]	0.0145 (0.0186) [0.7830]	0.0002 (0.0071) [0.0290]
Oil Futures t-1	0.0614*** (0.0180) [3.4040]	1.1069*** (0.0321) [3.3320]	-0.0706 (0.0485) [-1.456]	0.0096 (0.0186) [0.5180]
Loglik	-20957.4200			
AIC	2.9797			

Notes: Loglik denotes log-likelihood. Standard error is in ( ) and t-statistics is in [ ]. Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

Table 4.6 shows the volatility spillover among four markets. From these results, we can see that only freight price depends on its own lag volatility. In other words, the volatility of the shipping sector is strongly influenced by volatility in the previous day. We also observe the significance of Shipping Stock and Oil Futures coefficients, suggesting a spillover effect form shipping stock and oil to the freight market. There is no evidence supporting the existence of spillover effect volatility transmission among these three markets. As the shipping companies are oil consumption enterprises, and the change in oil price will lead to the change in the cost of the shipping companies including freight rate. The cash flows, as well as the production and management behavior, will be influenced by the cost, and last affect the enterprise value and stock market price.

In addition, the oil futures market exists the volatility spillover effect of the stock market. As one of the basic energy sources, the fluctuation of oil futures price will affect China's crude oil price and many industries such as the manufacturing industry and service industry, and then affect China's economy, causing the fluctuation of the

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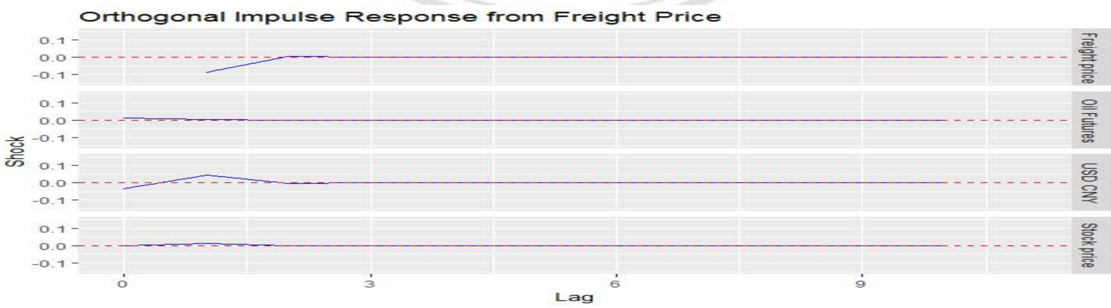
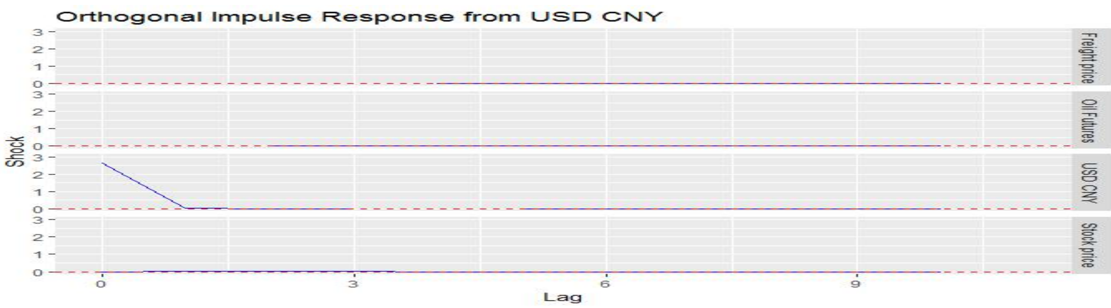
stock market. In particular, share prices in industries closely linked to oil futures react most quickly and strongly to the price of oil futures.

However, according to the small regression coefficient of Table 4.6, the relationship between these three markets is weak. This result corresponds to the copula dependence results which suggest a weak dependence among the shipping sector, oil futures, freight and currency markets. We thus conclude that low dependence among the markets may bring low volatility transmission among these four markets.

4.4.2 Estimate Results of Impulse Response Function

In order to estimate the response of the four variables when a shock is put to the error terms of the above VAR model, impulse response functions can be used. There are four variables in our VAR model and four impulse response functions can be used to explain to response among four variables. These are results by setting the variables given in R studio.





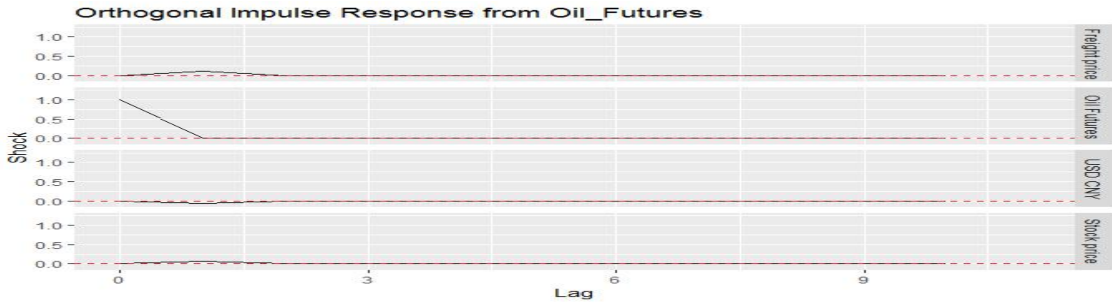


Figure 4.3: Volatility impulse responses

Finally, we undertake a more in-depth analysis of volatility transmission among the four markets. We concentrate more precisely on the dynamic volatility transmission and magnitude of a shock from one market to the other markets. This can be examined by the volatility impulse response function. Figure 4.3 depicts the impulse response among four markets. According to the results, four volatilities are positively small in response to their own shocks in the short term. In addition, the impact of the shock on the volatilities of shipping stock, oil futures, freight and currency are lower when compared to their own shocks. Indeed, the volatility in the four markets exhibits a smaller in magnitude. This finding may reflect that these four markets may not play an import role in each other.

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CHAPTER 5

Conclusions and the Recommendation

5.1 Conclusions

This paper employs the multivariate copula model and VAR model to estimate the dependence and volatility spillover among shipping sector stock index which is measured by SSE (Shanghai stock exchange) sector indices, Panamax freight price as measured by average chartering of 4 routes, the RMB/USD nominal closing exchange rate and WTI oil futures price. Our analysis consists of two parts. First, we investigate the dependence structures among these four markets using Copulas-based GARCH models with the skewed student-*t* distribution. In the second part, we use the VAR model and impulse response function to analyze volatility spillover among these four markets.

The main result of this part are:

1) The dependence correlation coefficients from the results of copula models show that four market volatilities display a weak degree of dependence. We find that the dependence between the shipping sector stock price and currency market is the strongest while the dependence between the freight market and oil futures market is the weakest.

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2) From the results of the VAR model, we can see that only freight price depends on its own lag volatility. In other words, the volatility of the shipping sector is strongly influenced by volatility in the previous day. We also observe the significance of Shipping Stock and Oil Futures coefficients, suggesting a spillover effect form shipping stock and oil to the freight market. There is no evidence supporting the existence of spillover effect volatility transmission among these three markets.

This result corresponds to the copula dependence results which suggest a weak dependence among the shipping sector, oil futures, freight and currency markets. We thus conclude that low dependence among the markets may bring low volatility transmission among these four markets.

3) According to the results of the volatility impulse response function, four volatilities are positively large in response to their own shocks in the short term. In addition, the impact of the shock on the volatilities of shipping stock, oil futures, freight, and currency are lower when compared to their own shocks. Indeed, the volatility in the four markets exhibits a smaller in magnitude. This finding may reflect that these four markets may not play an import role in each other.

5.2 Recommendations

Based on the above findings we have the following suggestions.

5.2.1 Internationalization of Securities Market

China has become the world's second-largest economy, playing an important role in the international financial market, and its stock market is the world's third largest capital market. China's stock market is the world's second-largest when companies listed overseas are included. The weak linkage between China's securities market and the international markets is not commensurate with the strength of China's economy and capital market. Therefore, the internationalization trend in China's securities market is imperative.

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To realize the internationalization of China's securities market, the government needs to strengthen the construction of the market system. Only when honest trading becomes the consensus of all market participants and the concept of practical action, can the market environment protect the interests of investors, drive the change of listed companies' concept of listing, promote the rational structure of market investors, and achieve the endogenous growth of the market. China's stock market still has a long way to go to achieve this.

In order to realize the internationalization of China's securities market, the government should also keep a look-out the international financial risks. The internationalization of the securities market inevitably increases the linkage between securities markets and the contagion effect of risks. Securities markets and even economic entities are more vulnerable to external shocks. Therefore, in order to realize the internationalization of the securities market, higher requirements are put forward for the wind resistance ability of China's securities market.

International securities markets depend on international economies. The internationalized economy is the economic basis for the internationalization of the securities market. Although China's economic aggregate is the second-largest in the world, China's economy is currently in a difficult process of structural transformation and industrial upgrading. Only by completing this process and making the overall economic operation more market-oriented can China's economy be considered an international economy. Realizing the internationalization of China's economy will inevitably lead to the internationalization of China's securities market.

5.2.2 Suggestions to China's Oil Market

The deregulation of oil price controls should be studied to make the oil market more market-oriented. The abnormal relationship between the oil futures market and the spot market is mainly caused by the control policy, which makes the hedging function of futures unable to play. But oil control policies also have a positive impact. On the one hand, it can help stabilize China's commodity prices and prevent risks from spreading from the international market; on the other hand, it is to stabilize China's oil prices, which is very important to China's economy.

The China's government should accelerate the development and establishment of the oil futures market to promote the reform of the oil pricing mechanism. In recent years, China's economy has become increasingly dependent on oil, but the essence of the pricing mechanism is still controlled by the government and not completely market-oriented. Through international experience, the only way to reform is to gradually open up the market of crude oil and refined oil and establish and develop the oil futures market. The government should establish and develop oil futures, give full play to their functions of price discovery, resource allocation and risk transfer in oil pricing, and improve China's position in the international oil market.

Since the link between oil and stocks is very weak, for most of the time, oil is not a good tool for investors to hedge shipping stocks. But investors can use the

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spillover effect between stocks and oil prices to adjust expectations and avoid a financial crisis.

5.2.3 Suggestions to Shipping Companies

First, shipping companies need to improve their judgment of the industry and market. In the past decade, although the shipping market has been at a low point for a long time, the number of ships built has not decreased but increased every year. On the one hand, too much money and investors are involved in this industry, which is caused by irrational investment and judgment. On the other hand, due to their inaccurate judgment of the industry, shipping companies do not realize that the shipping industry, as a derived demand of international trade, needs to pay attention not only to the situation of the industry but also to the situation of the world economy and international trade.

Second, shipping companies should use information technology flexibly to provide personalized services. With the gradual development of information technology, major shipping companies have launched their own e-commerce platforms, but there are still many areas for improvement in service.

Third, improve the financing capacity of shipping enterprises. Due to the large initial investment of shipping enterprises and the continued downturn of the shipping market, more and more enterprises are facing the risk of bankruptcy due to capital problems. Therefore, shipping enterprises should improve their financing ability, make flexible use of various financing methods.

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5.3 Future Study

Although this paper analyzes the spillover effect among stock, freight, oil and foreign exchange markets, it is still not perfect. This paper only selects four markets as representatives and fails to include more important financial markets. This problem can be overcome by expanding the research scope and sample size in future studies.

The data collection and processing in this paper is not perfect enough, which may cause the deviation of the results. In future research, these aspects will be further improved to obtain more accurate results.

In terms of method, we may try to use these two multivariate models of vine Copula or spillover index to study the relationship between multiple variables. Inevitably, our future work will center on these issues.

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