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The Risk Analysis of Chinese Refineries' Crude Oil Import Supply Chain

By

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Abstract

Crude oil trading is a daily-based transaction that constitutes one of the major trades of primary economic sector in every country. It is very important since it closely impacts the domestic energy security of a country. For refineries who are the main buyers and consumers of crude oil, they should be prudent when they import crude oil from a foreign country, since the trades often involve substantial amount of money. With the fact that China is becoming the largest crude oil importer worldwide and with the escalating turmoil in world crude oil supply, refineries in China are encountering more risks and uncertainties than before.

In this thesis, we will identify risks on both supply stage and transportation stage of the crude oil supply chain of Chinese refineries, and we will analyze the impacts of the risks towards the refineries. The methodology employed in this thesis is a composite indicator (CI) system and a Data Envelopment Analysis (DEA-like) model based on risk indicators. The model was run on Excel 2016 in the Solver Add-in. A four-sector analysis of CI scores and quantity of imports is conducted to provide a more comprehensive perception of the problem under study. Lastly, suggestions are provided to relieve impacts of the risks to the decision makers of the Chinese refineries.

Key words: Crude oil import supply chain; Chinese refineries; Composite indicator system; DEA-like model; Risk analysis.

Sommaire

Le négoce de pétrole brut est une transaction quotidienne qui constitue l'une des principales activités du secteur économique primaire dans tous les pays. C'est très important et cela a un impact majeur sur la sécurité énergétique nationale d'un pays. Les raffineries qui sont les principaux acheteurs et consommateurs de pétrole brut doivent faire preuve de prudence lorsqu'elles importent du pétrole brut d'un pays étranger, car les échanges commerciaux impliquent souvent d'importantes sommes d'argent. Avec le fait que la Chine est en train de devenir le plus grand importateur de pétrole brut au monde et que l'agitation dans le monde soit de plus en plus importante, les raffineries chinoises font face à plus de risques et d'incertitudes qu'auparavant.

Dans cette thèse, nous identifierons les risques à la fois au niveau des fournisseurs et du transport dans la chaîne d'approvisionnement en pétrole brut des raffineries chinoises, et nous analyserons les impacts des risques pour les raffineries. La méthodologie utilisée dans cette thèse est un système d'indicateurs composites (CI) et un modèle de type DEA *(Data Envelopment Analysis*) basé sur des indicateurs de risque. Le modèle a été exécuté sur Excel 2016 dans le module Solver. Une analyse en quatre secteurs des scores de CI et de la quantité d'importations est effectuée pour fournir une perception plus complète du problème étudié. Enfin, des suggestions sont proposées pour atténuer les impacts des risques sur les décideurs des raffineries chinoises.

Mots clés: chaîne logistique d 'importation de pétrole brut; Raffineries chinoises; Indicateur composite; Modèle de type DEA; Analyse de risque.

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List of Abbreviations and Acronyms

CI: composite indicator

COSC: crude oil supply chain

DEA: data envelopment analysis

DWT: deadweight tonnage

EIA: U.S. Energy Information Administration

HHI: Herfindahle-Hirschman Index

IMB: International Maritime Bureau

IRs: independent refineries

ITC: International Trade Centre

MCDA: Multi-criteria decision analysis

OECD: Organization for Economic Co-operation and Development

OPEC: Organization of the Petroleum Exporting Countries

R/P: reserve-to-production

SCRM: supply chain risk management

S&C America: South and Central America

UAE: United Arab Emirates

ULCC: ultra-large crude carriers

UK: United Kingdom

USA or US: United States of America

VLCC: very large crude carriers

WTI: West Texas intermediate

Acknowledgement

I would like to express my most sincere gratitude to my supervisor Professor Jacques Roy, who provided generous guidance and continuous support when I decided to change my thesis topic and when I hesitated over several methodologies. When I encountered difficulties and felt frustrated, his kind encouragement always revived my confidence to carry on.

I would also want to thank my family, who are always there to support and understand me.

The journey of learning at HEC Montréal would come to an end by finishing this thesis. However, the trip of lifelong learning has just started. I would like to express my deep appreciation to those people who helped me during my school time.

1. Introduction

1.1 Crude Oil Imports Worldwide

Crude oil is a critical and fundamental source of natural energy. Crude oil and its derivatives pertain to multitude aspects of a country's domestic manufacturing industries, transportation system, national security and even daily life to every citizen. Given its importance, international trade of crude oil is pervasive nowadays, with enormous amount of transactions accomplished on every day. From the Table 1.1-1 adapted from the BP Statistical Review of World Energy[1] in 2019, a steady increase of crude oil imports of the world total can be observed from 2009 to 2018, with an average annual growth rate of 1.9% from 2007 to 2017 and an annual growth rate of 2.5% in 2018. The amount of global crude oil imports reached 71.3 million barrels per day. Among all the countries and regions, China and India displayed the top two fastest rate of growth of 7.8% and 5.6% in 2018, accordingly. The lower part of the Table 1.1-1 demonstrates the supplier countries of crude oil. Among all the regions, Middle East countries exported the most significant share of crude oil, taking 34.5% of the total exports worldwide in 2018. North America, including Canada, the United States of America (US) and Mexico, contributed 18.2% of the total exports, following by Russia and other Commonwealth of Independent States countries which had a share of 15.8% of the total quantity of the global exportation. The growth rate of exports in the US accelerated rapidly in each year, and a rate of 21.7% was attained in 2018, indicating the fastest growth of exportation of crude oil across the world. An illustration that maps out the international movement of imports and exports of crude oil can be found in Figure 1.1-1, which is also adapted from the BP Statistical

[1] BP Statistical Review of World Energy in 2019 (last date of access: August 10th, 2019): https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html

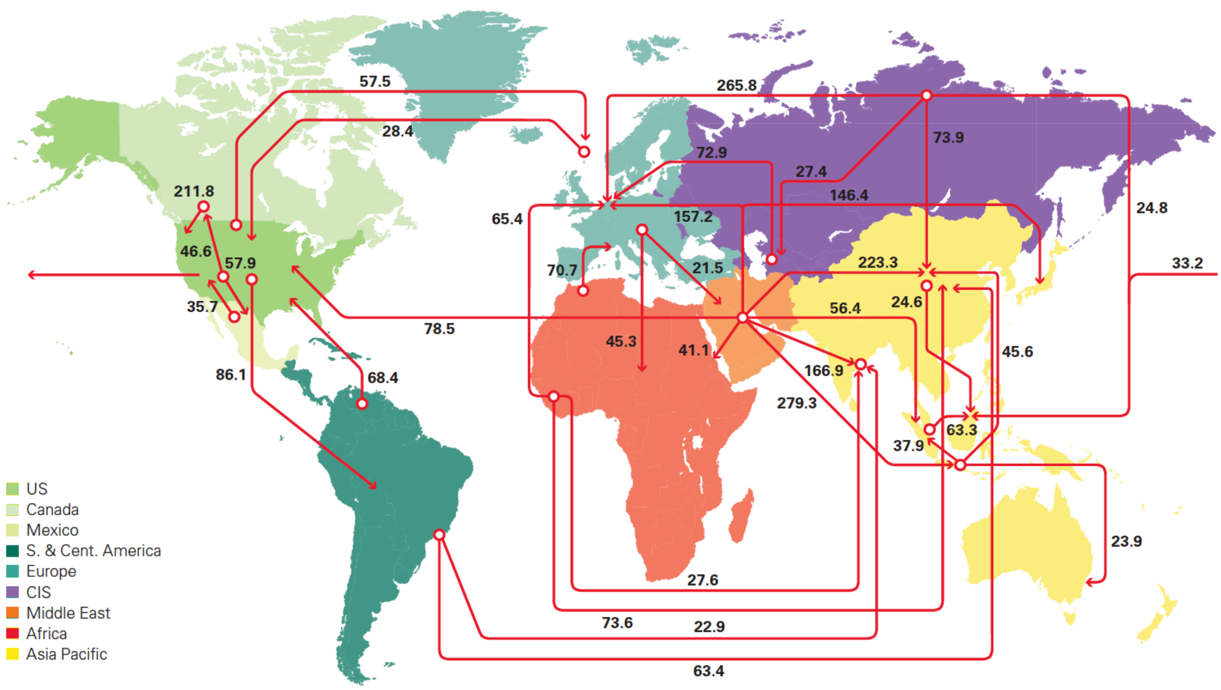
Review of World Energy[2] in 2019. From this graph we are able to confirm that the major suppliers of crude oil to the world are countries in the Middle East, Russia and in the North American area.

Table 1.1- 1 Import and export quantity of crude oil

Thousand barrels daily	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Growth rate per annum 2018	Growth rate per annum 2007-17	Share 2018
Imports														
US	12872	11453	11689	11338	10587	9859	9241	9451	10056	10148	**9929**	-2.2%	-2.9%	13.9%
Europe	14066	12802	12407	12489	12721	12920	12957	13993	14354	14699	**15124**	2.9%	0.3%	21.2%
China	4494	5100	5886	6295	6675	6978	7398	8333	9214	10240	**11039**	7.8%	9.4%	15.5%
India	3066	3491	3749	3823	4168	4370	4155	4380	4945	4947	**5223**	5.6%	5.4%	7.3%
Japan	4925	4263	4567	4494	4743	4637	4383	4332	4180	4142	**3941**	-4.8%	-1.9%	5.5%
Rest of World	17138	17211	17048	17634	17812	20012	21193	22026	23776	25457	**26087**	2.5%	3.9%	36.6%
Total World	56561	54320	55346	56072	56706	58776	59328	62515	66526	69633	71344	2.5%	1.9%	100.0%
Exports														
Canada	2498	2518	2599	2798	3056	3296	3536	3836	3890	4248	**4530**	6.6%	5.6%	6.3%
Mexico	1609	1449	1539	1487	1366	1347	1293	1323	1380	1300	**1360**	4.7%	-4.1%	1.9%
US	1967	1947	2154	2495	2682	3563	4033	4521	5078	5858	**7131**	21.7%	15.1%	10.0%
S. & Cent. America	3616	3748	3568	3755	3830	3790	3939	4107	4147	3992	**3745**	-6.2%	1.1%	5.2%
Europe	2073	2076	1966	2139	2181	2545	2467	2926	3082	3387	**3428**	1.2%	3.9%	4.8%
Russia	7540	7257	7397	7448	7457	7948	7792	8313	8814	8979	**9159**	2.0%	1.4%	12.8%
Other CIS	1730	1861	2039	2180	1962	2166	2092	2100	2096	2210	**2170**	-1.8%	3.5%	3.0%
Saudi Arabia	8357	7276	7595	8120	8468	8365	7911	7968	8606	8333	**8553**	2.6%	0.3%	12.0%
Middle East (ex S. Arabia)	12415	11744	11976	12188	11742	12242	12699	13537	15321	16183	**16087**	-0.6%	2.9%	22.5%
North Africa	3268	2943	2878	1951	2602	2127	1743	1701	1727	2214	**2486**	12.3%	-4.0%	3.5%
West Africa	4712	4531	4755	4759	4724	4590	4849	4880	4401	4582	**4572**	-0.2%	-0.8%	6.4%
Asia Pacific (ex Japan)	5392	5631	6226	6088	6299	6307	6450	6780	7356	7716	**7527**	-2.5%	2.5%	10.6%
Rest of World	1385	1340	653	663	338	491	524	525	625	632	**594**	-5.9%	-9.3%	0.8%
Total World	56561	54320	55346	56072	56706	58776	59328	62515	66526	69633	71344	2.5%	1.9%	100.0%

Table is adapted from BP Statistical Review of World Energy in 2019, Page 28 (last date of access: August 10th, 2019)

Figure 1.1- 1 Movement of import and export quantity of crude oil worldwide (in 2018)



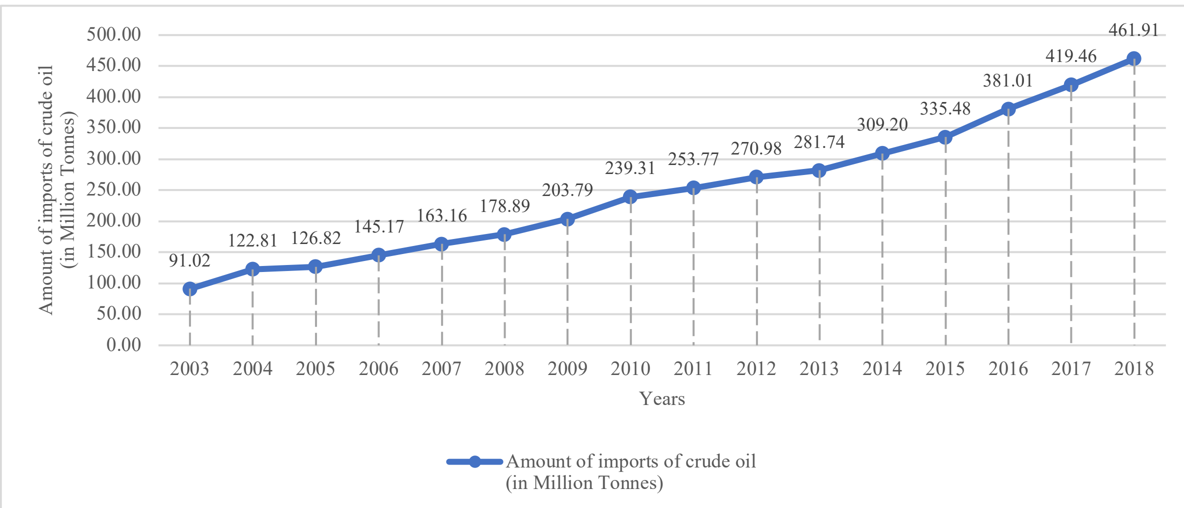
This figure is adapted from BP Statistical Review of World Energy in 2019, Page 29 (last date of access: August 10th, 2019)

[2] BP Statistical Review of World Energy in 2019 (last date of access: August 10th, 2019): https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html

1.2 Crude Oil Imports in China

China plays a significant role in global petroleum industry. As a result of its continuous economic development, the consumption and demand of petroleum products have been up surging in every aspect of daily life and in various industries. In this context, the amount of crude oil imported has been rising rapidly as well. It was in 1996 that China's crude oil imports amount first exceeded the exporting amount, making China a net importer of crude oil ever since (Wu, et al., 2009). In 2017, China exceeded the US and ranked first in importing crude oil (Table 1.1-1).

Chart 1.2- 1 Amount of imports of crude oil in China (from 2003 to 2018)

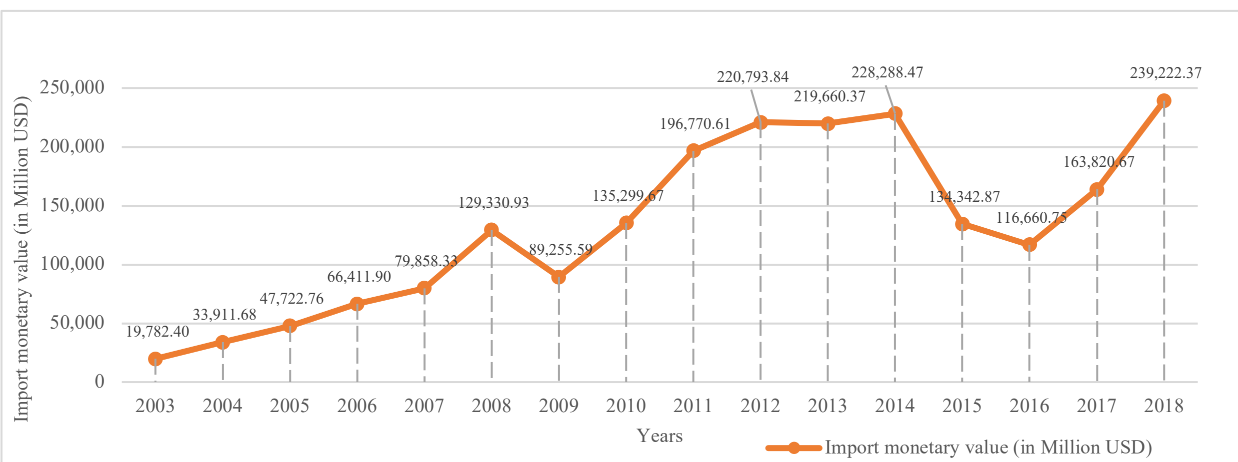


Source of data: International Trade Center (ITC) , http://www.trademap.org/Country_SelProduct_TS.aspx (last date of access: July 21st, 2019)

From the beginning of the 21st century to 2018, as shown in the Chart 1.2-1, the amount of crude oil imports experienced a fourfold increase from 91.02 million tonnes in 2003 to 461.91 million tonnes in 2018, with an average yearly growth of 11.66%. The most manifest growth was in 2004, when a growth rate of 34.93% appeared. Another significant growth in crude oil imports was in 2010 with a rate of 17.43%. After that, from 2016 to 2018, the growth rate in these three consecutive years exceeded 10% in each year, depicting an upward trend of crude oil imports in China. However, there was a noticeable slowdown in the growth rate. It happened in 2013, when the growth rate of crude oil imports dropped to 3.97%, which was at the lowest level ever since 2005. The main reason for the slackening of increment of crudes imports is that downtrend emerged in Chinese economy growth, resulting in less demand for petroleum products in all energy-intense manufacturing industries.

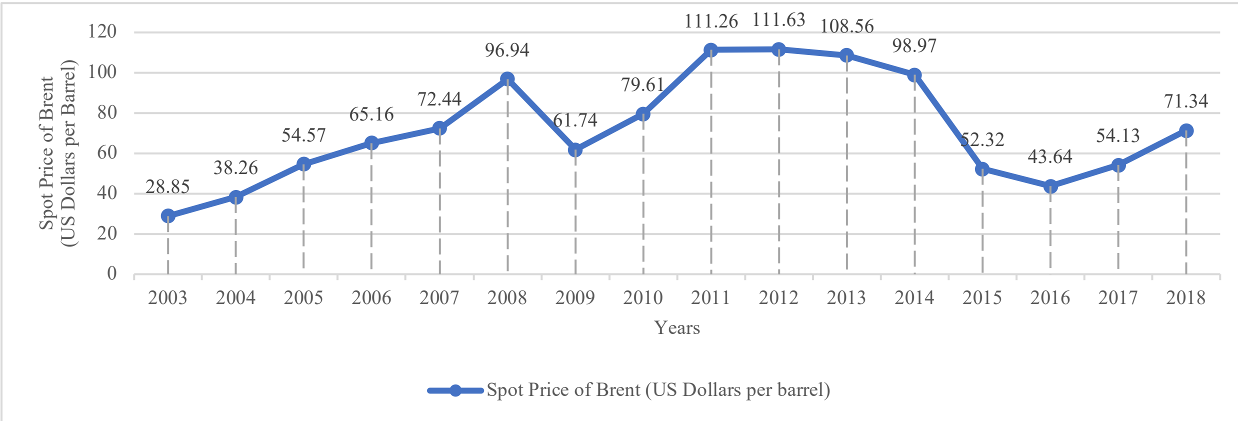
The monetary value, however, does not always incline during the period from 2003 to 2018. There are two obvious plunges, as shown in Chart 1.2-2. One was from 2008 to 2009, when the global economic recession created a low valley of the crude oil price of both Brent oil and WTI oil (in Chart 1.2-3 and Chart 1.2-4). Another one was from 2014 to 2016, when bubbles of the high oil price were thrust by a glut of crude oil. During that period, the blossom in production of shale oil in the US and overall less demand in other emerging countries led to excessive supply of crude oil that dragged down the oil prices. With a plunge of the oil prices (both Brent and WTI) from mid 2014 to 2016, China witnessed its shrinking monetary value on crude oil imports, even though the amount of imports increased continuously.

Chart 1.2- 2 Monetary value of imports of crude oil in China (from 2003 to 2018)



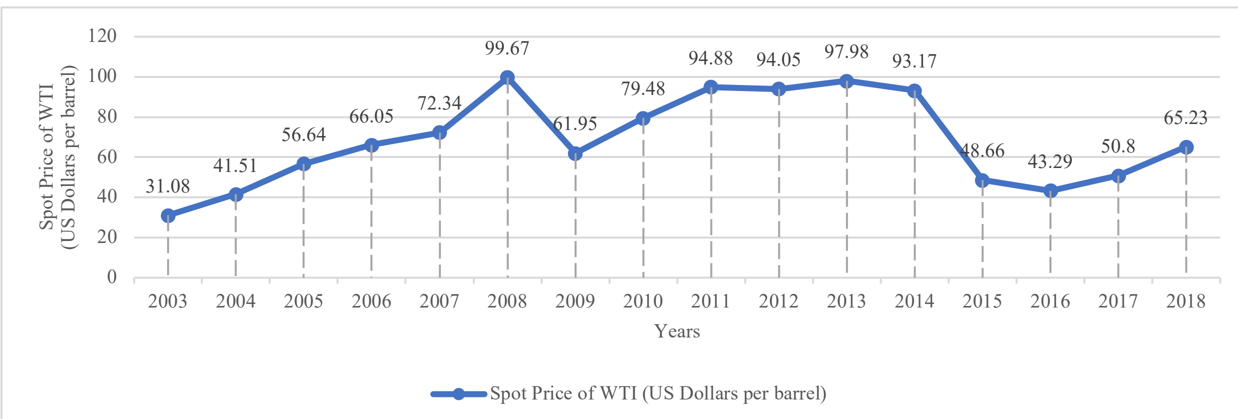
Source of data: International Trade Center (ITC) , http://www.trademap.org/Country_SelProduct_TS.aspx (last date of access: July 21st, 2019)

Chart 1.2- 3 Spot Price of Brent (Unit: US Dollars per barrel, from 2003 to 2018)



Source of data: the US Energy Information Administration (EIA) , https://www.eia.gov/dnav/pet/pet_pri_spt_s1_a.htm (last date of access: August 24th, 2019)

Chart 1.2- 4 Spot Price of WTI (Unit: US Dollars per barrel, from 2003 to 2018)

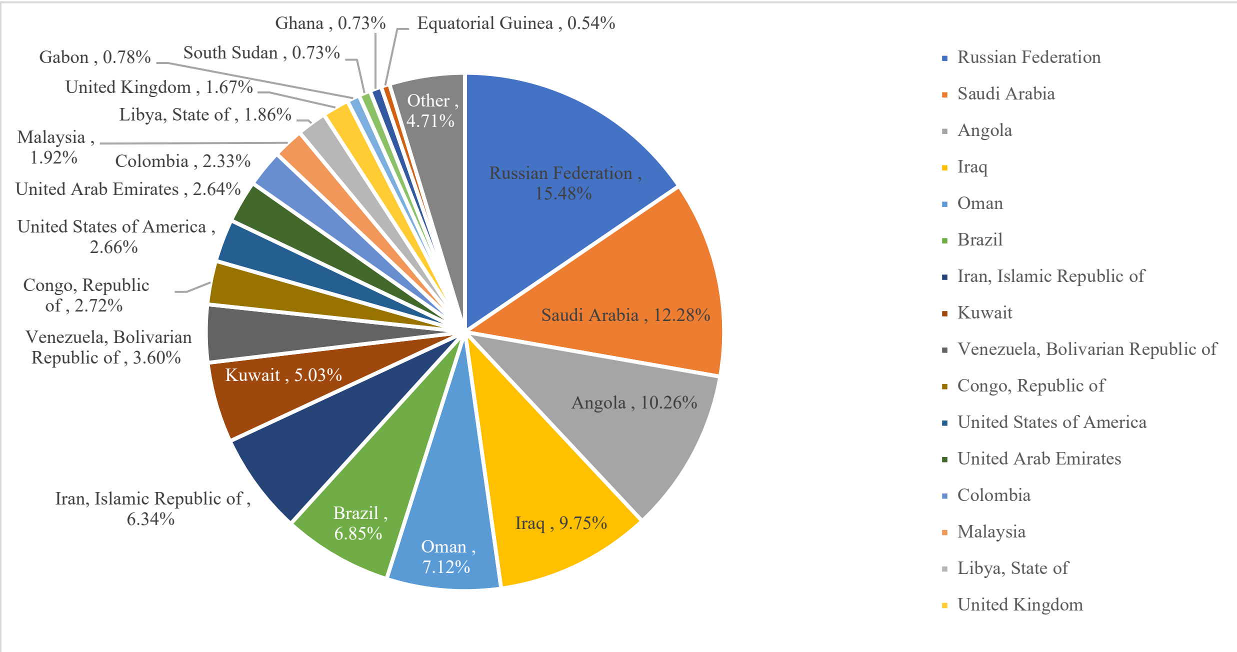


Source of data: the US Energy Information Administration (EIA) , https://www.eia.gov/dnav/pet/pet_pri_spt_s1_a.htm (last date of access: August 24th, 2019)

China imports crude oil from multiple countries in the Middle East, North Africa, South East Asia and South America, and the major supplier countries are as illustrated in a pie Chart 1.2-5. In recent years, Russia exports the majority of crude oil to China among all countries, due to geological adjacency and bilateral economic cooperation. In 2018, the amount of crude oil from Russia to China accounted for 15.48% of the total, and it has increased by 20.08% over the last year. Saudi Arabia and Angola are two other crude oil exporters of China, with a share of over 10% each in

2018. Iraq, Oman, Brazil, Iran and Kuwait are suppliers which contributed more than 5% of total imports in 2018. All of these eight countries made up 73.1% of total import in 2018.

Chart 1.2- 5 Suppliers and their share of crude oil imports (2018)



Source of data: International Trade Center (ITC) , http://www.trademap.org/Country_SelProduct_TS.aspx (last date of access: July 21st, 2019)

Locations of crude oil suppliers affect the transportation means and routes significantly. In general, suppliers in the Middle East contribute the largest share with 43.45% of total imports, followed by Africa which represents 19.46% of all imports. The next significant cluster of suppliers comes from central Asia and South America with percentages of 16.41% and 13.01% respectively[3].

Currently there are three international pipelines in operation in China, and they are China-Russia pipeline, Sino-Kazakhstan pipeline and Sino-Myanmar pipeline (Figure 1.2-1). These three pipelines delivered crude imports from central Asia, Middle East and Africa. Trains take part in

[3] Source of data: International Trade Center (ITC) , http://www.trademap.org/Country_SelProduct_TS.aspx (last date of access: July 21st, 2019)

crude oil transportation too, but they only carry very small amount of total imports from Russia, Kazakhstan and other central Asian countries. In recent years, the railway mode of transportation has gradually been taken over by the pipelines, since the pipelines have higher level of security and lower costs, and the pipelines have not reached their full capacity yet. In recent years, only approximately 10% of imported crude oil was transported by pipelines and railways (Sun, et al., 2017).

Figure 1.2- 1 International pipelines for crude oil imports and cities en route

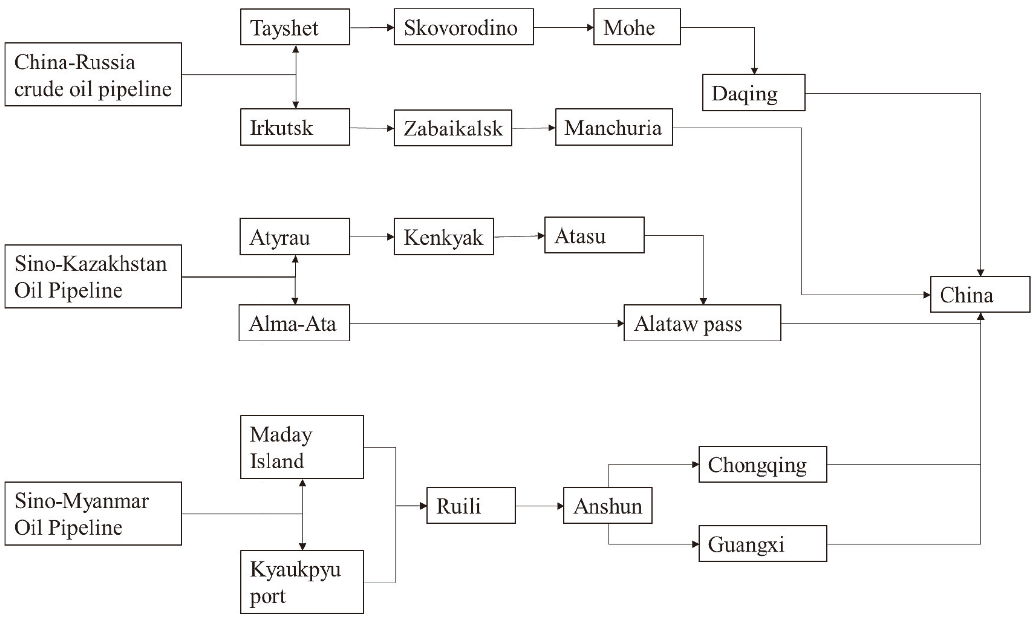
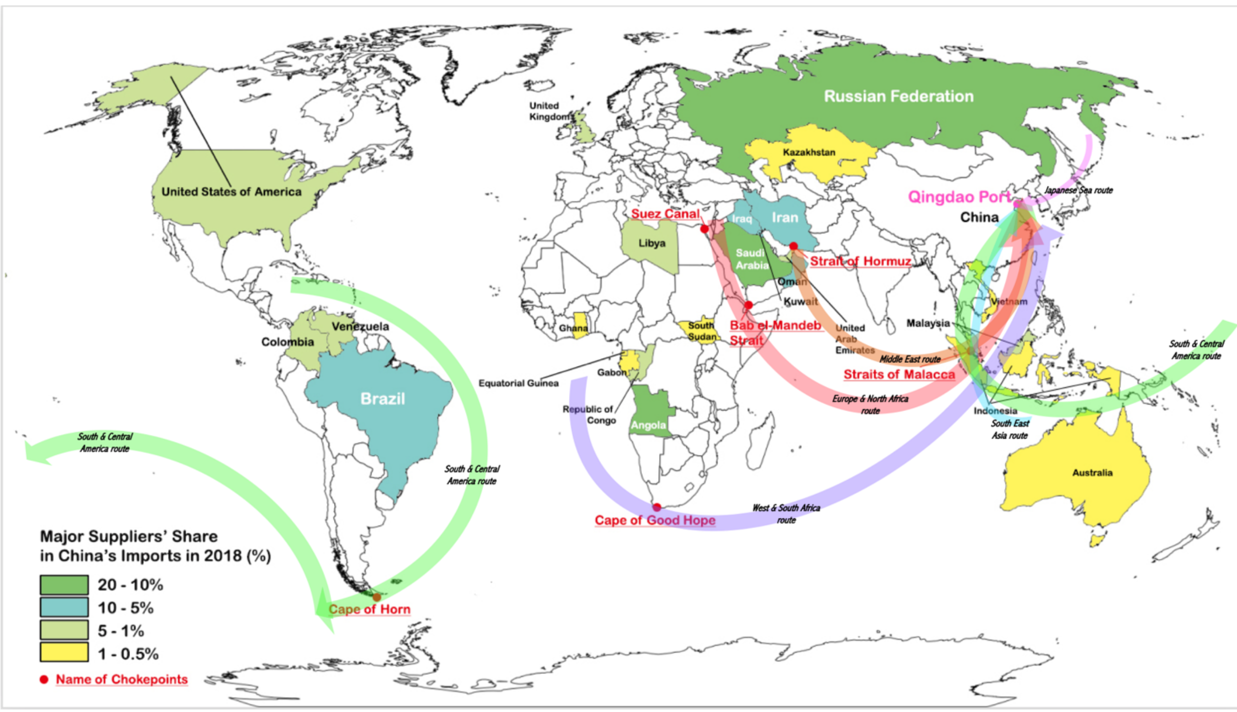


Figure is adapted from Sun et al. (2017), Page 456.

Besides crude oil pipelines and railway transportation, marine transportation is the primary mode when it comes to international and cross-continental transportation, accounting for about 90% of all imported crude oil (Sun, et al., 2017). Due to the locations of the crude oil origin countries, the principal routes can be classified as following (Figure 1.2-2) : a) Middle East line: Persian Gulf - Hormuz Strait - Straits of Malacca - South China sea; b) Europe and North Africa line: Suez Canal - Bab el-Mandeb Strait - Straits of Malacca - South China Sea; c) West Africa line: Cape of Good

Hope - Straits of Malacca - South China Sea; d) South and Central America line: North part of the South America - Cape of Horn - Pacific Ocean - Straits of Malacca - South China Sea; e) South East Asia and Pacific line: Straits of Malacca - South China Sea; and f) Japanese sea line: Japanese Sea - East China Sea. Apparently, on almost all main routes the oil tankers have to navigate through the Straits of Malacca in order to get to China. In recent years, for about 80% of all crude oil imported to China has to go through that chokepoint, indicating it is a critical one in the crude oil marine transportation (Sun, et al., 2017).

Figure 1.2- 2 Illustration of main marine transportation routes of crude imports to China



The oil tankers may arrive at different ports on the eastern coastline in China from south to north. There were 28 ports in 9 provinces that received tankers to discharge oil in 2018. Table 1.2-1 is a summary of the discharging information of the ports by provinces in 2018. The geographic locations of the ports can be found in Figure 1.2-3.

Table 1.2- 1 Quantity of discharged crude imports in each province (2018)

Province of discharge	*Discharge quantity (1,000 tonnes)*	*% of total*
Shandong	155,202.85	37.03%
Zhejiang	75,203.75	17.94%
Guangdong	59,928.68	14.30%
Liaoning	43,975.80	10.49%
Fujian	20,718.60	4.94%
Tianjin	19,035.65	4.54%
Hebei	16,866.49	4.02%
No information on discharging port	11,570.00	2.76%
Guangxi	8,920.00	2.13%
Hainan	7,681.26	1.83%
Grand Total	**419,103.08**	**100.00%**

Source of data: Traffic flow data from General Administration of Customs of China (published in 2019)

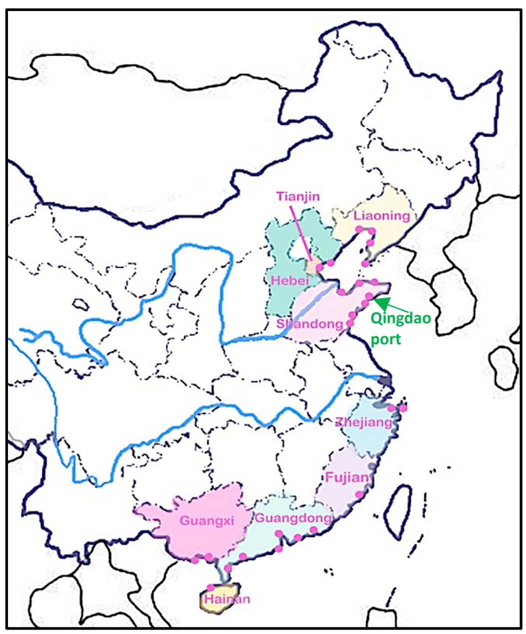
Of all provinces, Shandong province discharged the most of crudes in 2018 among all provinces, which are 155.2 million tonnes per year, comprising 37.03% of all crude oil imports by maritime shipment (Table 1.2-2). In Zhejiang province, 17.94% of all crudes were discharged, ranking number two in 2018. Guangdong and Liaoning come in number three and number four, with shares of 14.30% and 10.49% accordingly. Shandong province presents absolute advantage in the discharging amount in 2018, however, in 2015, it accounted for 25.54% of the total imports and Zhejiang province represented another 25.01%. When it comes to discharged tonnage of crudes, it can be observed from Table 1.2-2 that the discharged quantity in Shandong province grew for almost twice in 2018 than in 2015, while in Zhejiang province the quantity decreased 5.50% from 2015 to 2018. Another emerging province was Guangdong. The discharged quantity increased by 42.44% from 2015 to 2018, although the share of Guangdong slightly decreased in that period.

Table 1.2- 2 Comparison of quantities of discharged crude imports in each province (2015 vs. 2018)

Province of Discharge	Percentage of Total (%)			Discharged Quantity (1000 Tonnes)			
	2015	2018	Difference	2015	2018	Difference	Growth Rate
Shandong	25.54%	37.03%	11.49%	81,249.30	155,202.85	73,953.55	91.02%
Zhejiang	25.01%	17.94%	-7.07%	79,582.93	75,203.75	(4,379.18)	-5.50%
Guangdong	13.22%	14.30%	1.08%	42,072.82	59,928.68	17,855.86	42.44%
Liaoning	13.22%	10.49%	-2.73%	42,057.95	43,975.80	1,917.85	4.56%
Fujian	6.91%	4.94%	-1.97%	21,995.00	20,718.60	(1,276.40)	-5.80%
Tianjin	4.44%	4.54%	0.10%	14,117.78	19,035.65	4,917.87	34.83%
Hebei	4.46%	4.02%	-0.44%	14,200.75	16,866.49	2,665.74	18.77%
Hainan	3.71%	1.83%	-1.87%	11,793.30	7,681.26	(4,112.04)	-34.87%
Guangxi	2.57%	2.13%	-0.44%	8,175.00	8,920.00	745.00	9.11%
No record	0.92%	2.76%		2,912.84	11,570.00		
Grand Total	**100.00%**	**100.00%**		**318,157.67**	**419,103.08**	**100,945.41**	**31.73%**

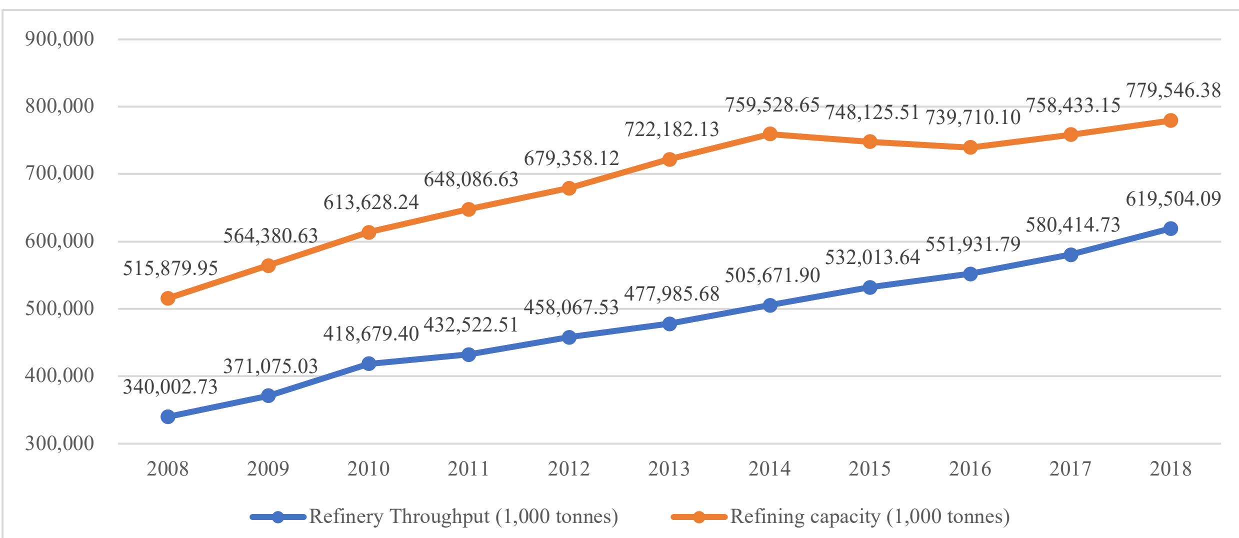
Source of data: Traffic flow data from General Administration of Customs of China (published in 2016 and in 2019)

Figure 1.2- 3 Geographic locations of provinces and ports of discharge



Generally speaking, the discharged quantity of crude oil imports in China raised by 31.73% from 318.16 million tonnes in 2015 to 419.10 million tonnes in 2018 (Table 1.2-2). The upward change in imports and discharged quantity is credited to augmentation in demand for crudes and in processing capacity of refineries in China. In 2018, refinery throughput of China has reached 12.44 million barrels per day, ranking number two worldwide behind the US, whose refinery throughput was 16.96 million barrels per day[4]. The throughput quantity is the actual amount of production, which reflects the demand. On the other hand, refining capacity shows that if all refineries and machinery are operative, the maximum amount of production can be achieved within a given period, indicating the processing capacity of refineries. Based on data provided by the BP Statistical Review of World Energy[4] in 2019, Chart 1.2-6 presents the refining capacity and throughput of refineries in China from 2008 to 2018. The refining capacity continually increased from 2008 to 2014, then with a slight decline from 2014 to 2016 and a moderate incline in the next two years. While being capped by the refining capacity, the refinery throughput of China depicted a constant upward trend growth from 2008 to 2018, and the quantity of throughput has nearly doubled in ten years.

Chart 1.2- 6 Refining capacity and refinery throughput of refineries in China (2008 - 2018)



Source of data: BP Statistical Review of World Energy in 2019): https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html (last date of access: August 10th, 2019)

[4] BP Statistical Review of World Energy in 2019 (last date of access: August 10th, 2019): https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html

Similarly, the rapid boost of discharged crudes in Shandong province reflected expanding demand. This increase can be explained by the release of crude oil import and process quotas in mid 2015 for the independent refineries (IRs) in China, and most of the IRs are in Shandong province. Over a few decades, although China has opened its crude oil trading market to the world, the right to import crude oil has been restricted the five state-owned corporations. The IRs had no choice but to buy more expensive fuel oil, which is different with crude oil, from international suppliers and crude oil from the five corporations. From 2001, crude oil import licenses had been gradually awarded to the qualified IRs, while the allowances were still highly restricted with conditions that the imported crude oil can only be sold to the state-owned companies. Thus, during that period of time, the IRs acted as trading companies without real processing quota of the imported crude oil. Eventually in July 2015, the quota of processing imported crude oil started to be distributed to several competent IRs. By the end of 2015, 13 IRs were granted the quota of processing, and 11 of them were in Shandong province. The quota is adjusted each year according to the performance and refining capacity of the IRs respectively. The number of IRs receiving quota has increased since then, as well as the total quota. Until 2018, 38 IRs were given quota and the total amount of quota surged to 109.41 million tonnes, among which 78.88 million tonnes were allocated to twenty-eight IRs in Shandong province (Table 1.2-3). Hence, the Qingdao - Rizhao port area in Shandong province acts as the key hub to the refineries.

Table 1.2- 3 Quota granted to IRs in each province and number of the IRs (2016 to 2018)

Provinces of IRs	*Sum of Quota in 2016 (in Million Tonnes)*	*Sum of Quota in 2017 (in Million Tonnes)*	*Sum of Quota in 2018 (in Million Tonnes)*	*Number of IRs with quota in 2016*	*Number of IRs with quota in 2017*	*Number of IRs with quota in 2018*
Shanxi	0	1.8	3.6	0	1	1
Shandong	56.89	60.12	78.88	16	25	28
Ningxia	6.16	0.59	2.16	1	1	1
Liaoning	7	7.14	12.8	1	2	3
Jiangsu	0	0	1.73	0	0	1
Hubei	0	1.15	2.3	0	1	1
Henan	0	1.11	2.22	0	1	1
Hebei	3.72	3.72	3.72	1	1	1
Fujian	0	0	2	0	0	1
Grand Total	**73.77**	**75.63**	**109.41**	**19**	**32**	**38**

Source of data: General Administration of Customs of China

The sudden upsurge of demand for the imported crude oil caused massive pressure not only on the crude oil import supply chain of IRs, but also on that of all refineries in China. The increasing demand requires the refineries to search for more suppliers and reliable sources of crude oil, leading a more competitive environment to all refineries in China. Risks of whether the refineries can obtain sufficient and continuous source of supply may emerge on this stage. Transportation of crude oil can be full of risks too, due to explosive nature of crudes as well as high value and massive volume of the cargoes, and long distance of international transit routes. According to Sun et al. (2017), foreign tankers conducted about 90% of international crude oil transportation to China, enforcing the transportation of imported crude oil to be in a rather vulnerable situation.

Thereupon, following problems will be discussed in our thesis. Firstly, what are the risks in the crude oil import supply chain of refineries in China, and how do the risks affect those refineries; secondly, what suggestions can be provided to the decision makers of the refineries, in order to relieve the impacts of the risks emerged.

Based on the problems stated above, the structure of this thesis is revealed as follows. In section one, a general introduction is provided on crude oil importing business worldwide and in China. In section two, relative literature and papers are reviewed. Section three presents the methodology and models that we use in this thesis, which is a composite indicator (CI) system and a DEA-like model based on indicators. In this section, risk indicators on each stage of the crude oil import supply chain are identified, and then normalization methods are discussed, and finally the DEA-like model is introduced. In section four, the process of data collection is described, as well as a preliminary analysis on each indicator is given. Also, in this section, a case study on Chinese refineries' crude oil import supply chain is conducted, applying the models and data on hand. Section five comes with suggestions that can help to relieve impacts of the risks for the decision makers in the Chinese refineries. Last but not least, conclusion is presented in section six.

2. Literature Review

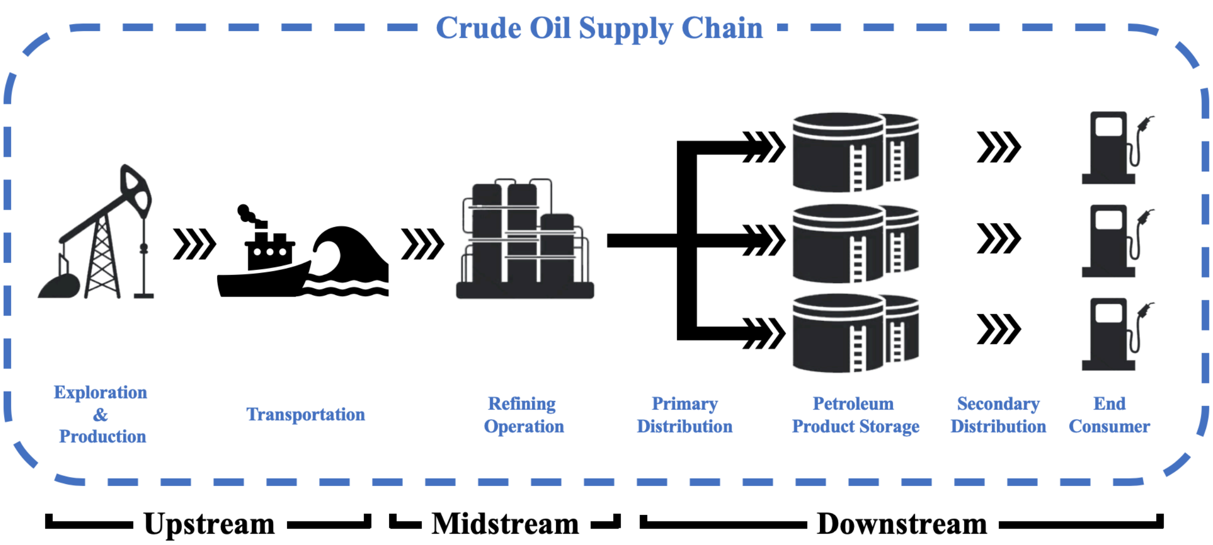
In this section, a review of literature pertaining to our problem is provided. The research articles are selected and examined from several aspects. First, similar to other industries, the crude oil industry comprises various activities, and the network of these activities forms a unique supply chain of the crude oil industry. Any entity, no matter if a country or a company, involved in this supply chain is profoundly affected by it. For this reason, an introduction to the crude oil supply chain (COSC) will be given. Secondly, risk management in a supply chain is discussed. Then, research papers on risk management under the context of COSC are reviewed. During this phase, quantitative methods of risk analysis on the COSC are discussed, with our focus on the Composite Indicators (CI) approach and data envelopment analysis (DEA) approach.

2.1 Crude Oil Supply Chain (COSC)

Along with the rapid progress of global industrialization, crude oil industry requires coordination and cooperation across the world. International oil companies and refiners increasingly rely on crude oil imports from oil reservoirs in foreign countries, as well as expand their business to overseas markets through international investment and exportation. Other entities who possess surplus crude oil may export the crudes and import refined petroleum products. On each stage of the crude oil industry, there are many players who interact based on their own interests. Thus, the supply chain of crude oil industry has become one of the most complicated industry networks, with great complexity and intense competition (Sahebi, et al., 2014). Comparable to the definition of supply chain in other industries, the crude oil supply chain (COSC) can be defined as "the entire process by which oil consumers acquire oil from external suppliers to meet import demands through trade, and trade oil is eventually transported to the consumers" (Zhang, et al., 2013, page 87).

Activities included in the COSC are, from the origin to the end, exploration and production, crude oil transportation, refining operations, primary distribution, petroleum product storage, secondary distribution and finally to the end consumer markets (Hussain, et al., 2006). An illustration of the activities is shown in Figure 2.1-1.

Figure 2.1- 1 Main Activities in Crude Oil Supply Chain and Segments of the Supply Chain



This figure is made based on information in the paper of Hussain, et al. (2006), "*Supply Chain Management in the Petroleum Industry: Challenges and Opportunities*"

Segmentation of the COSC has been discussed for a long time; however, opinions do not come to a single conclusion. According to Sahebi et al. (2014) and Lima et al. (2016), the COSC can be divided into three segments – upstream, midstream and downstream. The upstream encompasses crude oil exploration, production, acquiring crude oil and transportation to the refineries. The midstream is the transformation of crude oil into other petroleum products in refineries. The downstream involves the rest of the activities, from primary distribution process to the sale to end consumers. Hussain et al. (2006), however, proposed another classification. They divided the supply chain into upstream and downstream, where the upstream includes exploration to crude oil transportation, while the downstream contains the other activities, starting from the refining operations. The same classification is mentioned by Fernandes et al. (2009).

The main focus of our study is to analyze supply chain risks for the refineries in their import and transportation process, which is classified as upstream activities in both segmentations. In our paper, we assume all of the refineries are fed by the imported crude oil. Therefore, in this paper, the term 'upstream' should be used from the viewpoint of the refineries that purchase and import crude oil from their supplying countries and transport it by leasing third-party spot-chartered oil tankers.

2.2 Supply Chain Risk Management (SCRM)

Risk evaluation and control within a supply chain is usually achieved by risk management approaches. The supply chain risk management (SCRM) was defined as "the management of supply chain risks through coordination and collaboration among the supply chain partners so as to ensure profitability and continuity", in Tang's article (2006, page 453). According to the author, supply chain risks could be divided into operational risks and disruption risks. The former ones were referred to as systematic risks that arise within supply chain, while the latter ones represented risks from the external environment. The author believed that business impact derived from the external world was greater than that of systematic ones. Means of risk mitigation could be assorted based on different activities in a supply chain. Tang et al. (2006) proposed four basic approaches to alleviate the impact of risks, which were supply management, demand management, product management and information management. Each of them dealt with inter-related risk issues and their sub-issues. Similarly, Tang and Musa (2011) reviewed SCRM related literature from 1995 to 2008, summarizing that the major risk issues in a common supply chain were classified into material flow risks from suppliers to end consumers, financial flow risks in a reverse direction, and information flow risks along all supply chain. Based on research papers of Tang et al. (2006) and Tang and Musa (2011), we compare and combine the two ways of classification. As shown in Table 2.2-1, which lists the risk issues in each category:

Table 2.2- 1 Risk Issues in A Supply Chain

Category	***Risk issues***	***Risk Sub-issues***
Material Flow Risk	Supply	Single Sourcing Risk
		Sourcing Flexibility Risk
		Supply Product Monitoring/ Quality
		Supply Capacity
		Supplier Selection/ Outsourcing
		Supplier Relationships
		Supply contracts
	Product	Product and Process Design Risk
		Production Capacity Risk
		Operational Disruption and Postponement
	Demand	Demand Volatility Across Time, Markets and Products
		Balance of Unmet Demand and Excess Inventory
	Supply Chain Scope	Logistics
		Price Volatility of Commodity/ Alternative Energy
		Environment Degradation and Awareness
		Political Risk
		Cultural and Ethics Supply Chain Partners Relationship
Financial Flow Risk		Exchange Rate Risk
		Price and Cost Risk
		Financial Strength of Supply Chain Partners
		Financial Handling and Practice
Information Flow Risk		Information Accuracy
		Information System Security and Disruption
		Intellectual Property and Information Outsourcing

Content of this table is based on information provided in research papers of Tang et al. (2006) and Tang and Musa (2011).

To measure the risks in a supply chain, researchers have suggested multiple approaches. In Beamon's (1998) work, the author classified the approaches into four categories: deterministic analytical models, stochastic analytical models, economic models and simulation models, based on whether or not input variables are known and whether an approach is mathematical (the first two models) or non-mathematical (the last two models). Sahebi et al. (2014) only considered mathematical models in their study, therefore they omitted the economic and simulation models. The authors defined the classification of approaches based upon four criteria: linear vs. nonlinear models, continued vs. (mixed) integer variables, single vs. multi-objective functions, and deterministic vs. stochastic models. Heckmann et al. (2015) conducted a literature analysis on supply chain risk management approaches. The authors utilized and developed the classification proposed by Sahebi et al. (2014) , and they concluded that most of the reviewed papers employed mixed integer linear programming models, with rare use of non-linear approaches. Qualitative approaches were summarized in Tang and Musa's (2011) research, corresponding to each risk issue they listed as shown in Table 2.2-1. They suggested alternative sourcing for the supply risks, lean manufacturing for product and demand risks, operational hedging for financial risks, etc.

2.3 Risk Management in Crude Oil Supply Chain (COSC)

Under the context of our problem, the crude oil refineries confront various risks and uncertainties in the upstream activities, such as risks in supplier selection, supply reliability, sourcing flexibility, transportation security, etc. They also need to face exogenous risks or unexpected events such as natural disasters, manmade accidents or errors, economic or political mutation in supplier countries, significant fluctuation in oil price and tanker leasing rate, and so on. Thereupon, we segment the upstream COSC in two stages: 1) a supply stage and 2) a transportation stage. Firstly, we will review studies on risk management in the whole COSC, without being confined to the upstream supply chain, in a general manner. Then literature regarding risk assessment on the supply stage and transportation stage of the upstream COSC is reviewed. The literature review we deliver may not be exhaustive, and any omission is meant to be unintentional and with sincere apologies.

2.3.1 Risk Management in Whole Crude Oil Supply Chain (COSC)

Many articles on risk management of the COSC were published during the last decades. They cover a large scope, and the techniques used have evolved swiftly. When searching for pertinent research papers, we applied several keywords such as "*supply chain*", "*risk management*", "*energy security*", and "*crude oil*". Those words were used solely or in conjunction with one another.

Overall, most scholars concur that the risk management in the COSC is vitally essential. Guarantee of stable and sufficient crude oil supply facilitates a healthy growth of a country's economy, since the products from the petroleum industry support most of economic activities in a country. Nonetheless, COSC risk management can be very challenging too, because "the petroleum industry supply chain logistics network is very inflexible due to production capabilities of crude oil suppliers, long transportation lead times, and the limitations of modes of transportation" (Hussain, et al., 2006, page 91). Also, the COSC is "inserted in an unstable context, influenced by geopolitical unrest, global competition and price volatility", as asserted by Lima et al. (2016, page 79).

Analogous to the risk classification and risk issues in generic supply chain risk management, risks within COSC are classified according to demand side risks, supply side risks, regulatory risks, infrastructure risks and catastrophic risks (Wagner & Bode (2006) and Fazli et al. (2015)). Demand side risks include risks of oil price fluctuation and demand shock from the market, transportation modes and accidents or piracy attacks (Gupta, 2008), as well as fierce competition among producers with more advanced technologies (Jessen, 2008). Supply side risks refer to risks during exploitation and production process (Shebeko, et al., 2007) and quality risk of crudes extracted. Regulatory risks appear when regulations promulgated by governments or actions taken by international organizations, such as the Organization of the Petroleum Exporting Countries (OPEC), that may be against any party in the COSC (Fazli, et al., 2015). Environmental risks, for example oil spill, are classified into regulatory risks by Fazli et al. (2015). Infrastructure risks indicate information system failure and malfunction of machine that may result in postponing production (Adhitya, et al., 2007). Lastly, catastrophic risks involve natural disasters, such as earthquakes and hurricanes, piracy attacks and vandalization (Cordesman & Al-Rodhan, 2005), and socio-political unrest, for example subversion of a regime (Fazli, et al., 2015).

Methods that have been applied to assess risks of the COSC kept evolving in the past decades. Fernandes et al. (2009) reviewed both earlier works from several decades ago and recent studies on risk management under the context of COSC. They discovered that in the earlier works, qualitative methods were commonly used; however, in the recent studies quantitative approaches are preferred by scholars. The qualitative approaches differ from one another, and it is hard to summarize in a limited space, due to uniqueness in each case. Some examples are fault tree analysis, contingency plans and case hierarchy diagrams, etc. With developments in the mathematical programming techniques, in the mid-2000, a shift of concentration from qualitative methods to quantitative methods appeared. In a range of quantitative methods, risks can be quantified as variables or constraints in a mixed integer linear program (as in Rocha, et al. (2009) and Neiro & Pinto (2004)), in stochastic approaches (as in Khor et al. (2008), Tong et al. (2012) and Oliveira et al. (2016)), and in Multi-Criteria Decision Analysis (MCDA) (as in Enyinda et al. (2011) and Fazli et al. (2015)), etc. Since our focus is on the supply transportation stages, the methods used in overall COSC risk management will not be discussed too much in details.

Amor and Ghorbel (2018) reviewed papers from a perspective of countries contributing to COSC risk management and found that different countries focus on various activities or stages of the COSC. They concluded that, countries that rely on external oil supply focus on import and supply stage, such as European countries, China and the USA; while countries like Brazil, Iran and Thailand contribute more research on refining operations and production; finally, papers analyzing risk management in China and Nigeria concentrate on the transportation and distribution stages of their COSC.

2.3.2 Risk Assessment on Supply Stage and Transportation Stage

With the purpose of narrowing down our searching scope, we added "*upstream*", "*supplier security*", "*import*", and "*transportation*" into the keyword filter. The keywords helped us to exclude articles on crude oil exploitation and production, as well as articles on problems in midstream or downstream of the COSC. Therefore, literature on the upstream COSC, which comprises both the supply stage and the transportation stage, are sorted. In the papers we have reviewed, methods and risk factors can be shown in the Table 2.3-1:

Table 2.3- 1 Methods and Risk Factors in Reviewed Papers

Author(s)	Year	Stage of COSC	Methods	Risk Factors
Stringer	2008	Supply stage	Portfolio approach	Supply source diversification
Vivoda	2009	Supply stage	Portfolio approach	Systematic indicators: Level of instability of oil exporters; Exporter concentration; Supply disruptions; Non-market strategies Country-specific indicators.
Li et al.	2014	Supply stage	Multi-objective programming approach	Country risk of suppliers; Supply source diversification
Hassani et al.	2017	Supply stage	Semi-Quantitative approach and Monte Carlo simulation	Early start-up of projects; Oil market and oil price volatility; Field output reduction in decline or acceleration; Technical improvement; Geopolitics and unrest; Delay on start-up or ramp-up; Conservative fiscal regime; Unplanned shutdowns; Weather conditions
Shao et al.	2017	Supply stage	Log-linear panel data model	China’s crude oil imports dependency; Oil supply and demand stability; Oil price volatility; Oil trade openness; Bilateral trade relationship; Geographic distance; China’s direct investment; Political risk of suppliers
Li et al.	2015	Transportation stage	Bi-objective programming approach, and Intellectual Knowledge Management	Country risk; Route risk; Duration on route
Siddiqui et al.	2014	Transportation stage	Bi-objective mixed-integer optimization model	Oil spill risk; Operational cost of fleet
Siddiqui et al.	2015	Transportation stage	Bi-objective mixed-integer optimization model	Oil spill risk; Operational cost of fleet
Wang and Lu	2015	Transportation stage	Bi-objective programming model	War and regional conflict; Geopolitics and international situation; Terrorism and pirates; Import source stability; Transportation distance; Weather and sea state; Traffic capacity
Douligeris et al.	1997	Transportation stage	Bayesian hazard assessment module	Oil spill and pollution

Table 2.3-1 (continued) – Methods and Risk Factors in Reviewed Papers

Zhang et al.	2013	Supply stage and transportation stage	Data envelopment analysis (DEA)	Ratio of oil imports to world total oil imports; Geopolitical oil supply market concentration; Dollar index volatility; Oil price volatility; Ratio of vale of oil imports to GDP; Trade route risk; Oil import dependence; Diversification of oil import source
Sun et al.	2014	Supply stage and transportation stage	Composite Indicators (CI) and data envelopment analysis (DEA)	Weighted average of political; Economical and financial risk; Average number of pirate attacks
Mohsin et al.	2018	Supply stage and transportation stage	Composite Indicators (CI) and data envelopment analysis (DEA)	Ratio of imported oil to GDP; Geopolitical risk; Market liquidity; GDP per capita; Ratio of oil imports to consumption; Diversification; Oil price volatility; US$ volatility; Transportation risk
Yang et al.	2014	Supply stage	Composite Indicators (CI)	Diversification of oil import sources
Sun et al.	2017	Supply stage and transportation stage	Composite Indicators (CI)	Country risk; Potential exports ability; Geographic distance; Share of each route; Probability of disruption in each route; Annual total imports; Port infrastructure; Emergence management capability; Oil price volatility; GDP of the importer

Since we intend to solve a problem regarding both the supply stage and the transportation stage, during our literature review, we found that the Composite Indicators (CI) and data envelopment analysis (DEA) were applied to either or both supply stage and transportation stage, which coincides with our aim. Thus, the papers utilizing either or both methods attract our interests, and they will be reviewed in detail. Other research articles also contribute generously to the risk management on supply stage and transportation stage of the COSC, however, they are not the focus of our study in this paper. Hence, those articles will be summarized in brief, just to provide readers with a sense of research directions.

As shown in Table 2.3-1, on the supply stage, scholars applied parametric approaches, such as multi-objective programming models (Li, et al., 2014), log-linear models (Shao, et al., 2017) and simulation (Hassani, et al., 2017), as well as non-parametric approaches, for instance DEA-like models (Zhang, et al. (2013), Sun, et al. (2014), and Mohsin, et al. (2018)), Composite Indicators (CI) approach (Yang, et al. (2014) and Sun, et al. (2017)) and portfolio approach ((Stringer (2008) and Vivoda (2009)). While on the transportation stage, researchers employed methods such as bi-objective programming model (Li, et al. (2015), Siddiqui et al. (2015) & (2014), and Wang and Lu (2015)), Bayesian hazard assessment module (Douligeris, et al., 1997), as well as CI and DEA approaches, which we will discuss in later paragraphs.

2.3.2.1 Risk Assessment on Supply Stage

Li et al.'s (2014) introduced a multi-objective programming method, which is a type of optimization problem that contains trade-offs between objectives, which are minimizing import costs and reducing risk exposure. The model in this paper uses country risk as a main objective to minimize impacts of some extreme events on risk exposure and import costs, in order to provide an optimal diversification policy.

A statistics-based approach was used in order to quantify the uncertainty of crude oil supply in short-term periods (Hassani, et al., 2017). Two quantitative approaches are introduced: semi-quantitative approach and Monte Carlo simulation. They are both based on a risk matrix, which is weighted by the oil supply share of each country. The Monte Carlo simulation provides a probability distribution for the uncertainty of future supply.

Shao et al. (2017) intended to identify the determinants of the crude oil trading pattern of China's oil importing activities, and to measure how much do the determinants affect the pattern. The authors collected data from 55 countries that export crude oil to China for 3 years, from 2012 to 2015. They applied a dynamic panel data approach and built a static model. In the static model, a log-linear panel data model and the correlation for the variables were provided. Based on existing studies, the authors proposed eight hypotheses for each influencing risk factor and whether it has positive or negative impact on China's crude oil imports.

Portfolio approach was suggested by Stringer (2008) and Vivoda (2009). Stringer (2008) proposed an empirical measurement of risks by diversification of energy resources and suppliers. The oil supply risks are quantified by risk indices. Vivoda (2009) presented systematic indicators, such as level of instability of oil exporters, exporter concentration, supply disruptions, and non-market strategies. Moreover, country-specific indicators for the US, Japan and China, such as oil import dependence ratio, total oil imports, change in total oil imports, Middle East oil import ratio and non-regional oil import ratio were analyzed by using portfolio approaches.

2.3.2.2 Risk Assessment on Transportation Stage

Siddiqui et al. (2014) asserted that due to the hazardous nature and alluringly high value of crude oil, there could be many risks arising during transportation. In more and more recent research, transportation risk is linked to operational costs, usually forming a bi-objective optimization problem. The problem can be solved by models that are designed to minimize both risks and costs, leading to a trade-off between the risks and costs.

Li et al. (2015) studied risk integration in maritime system, by building a bi-objective programming model, incorporating both country risks and transportation risks as total risk. Two objectives, to minimize total risk exposure and to control costs, were set separately as two functions in this model, while minimization of risk exposure comes prior to that of cost. A Multi-Objective Particle Swarm Optimization algorithm was adopted to solve the bi-objective problem. This methodology was based on intellectual knowledge management, which was a tool to enhance data mining and thus to optimize oil-import portfolio and reduce risks. The authors discovered that transportation risk and country risk shared positive correlation, while the increase of transportation risk might affect multiple supplier countries.

Analogously, Wang and Lu (2015) established a bi-objective programming model to minimize transportation cost and to minimize overall risks. Unlike in the previous paper, the authors proposed a genetic ant colony algorithm to solve the problem, due to the NP-hard nature of the model. In this paper, the authors considered not only maritime transportation, but also pipeline transportation of crude oil in China. As a result, very large crude carriers (VLCC) were proven to perform better in long-haul maritime transportation, however, with a higher level of risk compared to pipeline transportation.

Differentiated from the previous two articles, Siddiqui et al. (2014) incorporated both operational cost of the fleet as well as potential risks of oil spill as two objectives. The potential cost related to oil spill was calculated. Bi-objective mixed-integer optimization method was adopted to solve the problem, from an oil supplier's perspective. They discovered that oil spill risk played an important role in their case. Neglecting that risk could cause significant potential loss. In a similar manner, in their work in 2015, Siddiqui et al. (2015) built a bi-objective mixed-integer optimization model to discuss further on oil spill risk versus costs. After considering oil spill risk and its correlated costs, the route with the shortest distance would not necessarily be the one with least expenses. The authors claimed that traffic condition could be worse on the shortest route, compared with the longer routes. The reason behind this was that accidents would appear more frequently on the shortest route, resulting in a higher level of risk. The authors suggested that if management values risk more, then they should use larger ships on less risky routes, because the larger ships would have less trips, given a certain amount of crude oil. Hence less chance to encounter risks. Moreover, if risk is weighted as critical, then all vessels should travel through less risky routes.

Another paper on oil spill risk assessment was written by Douligeris et al. (1997), who introduced a model which depicted a whole transportation system and contained a feature of Bayesian hazard assessment module. This module included three parts: a hazard assessment module to come up with a distribution of oil spill based on historical data; an exposure assessment module to estimate volume of oil spill and its impact; and a response assessment module to generate a response measure. To compute the oil spill hazards, the number of spills and the size of each spill were taken as variables and they were assumed to follow a Poisson process. The distributions of both variables were combined to formulate a compound distribution, based on which the oil spill hazard was estimated.

2.3.2.3 Risk Assessment using Composite Indicators (CI) and Data Envelopment Analysis (DEA)

The Composite Indicators (CI) are defined by the Organization for Economic Co-operation and Development (OECD) as "A composite indicator is formed when individual indicators are compiled into a single index, on the basis of an underlying model of the multi-dimensional concept that is being measured" in the OECD Glossary of Statistical Terms[5]. The CI is widely used to generate a more comprehensive index. Examples of CI application can be found in Human Development Index by the United Nations (UN), World Income Inequality Database: Gini Index by UN, Doing Business Indicators by World Bank, etc. It also becomes a useful tool when comparing performance among countries, based on the indicators of each country. Outstanding features of this method include that it can summarize complex and multi-dimensional indicators into one composite index, entailing comparison among different entities; it allows multi-period comparison of entities; it combines various indicators without losing their inherent information base (OECD, 2008).

In spite of all the advantages mentioned above, the CI system has been regarded as controversial since it was first introduced. Criticism of lack of objectivity is attributed to the "synthetic" indicators and weights that are allocated to the indicators. Selection of indicators is based on the analysts' knowledge and subjective judgment, while assigning fixed weights is criticized by Cherchye et al. (2007, page 115) as "that subjective judgments about the relative 'worth' of each of the sub-indicators enter through the weights". The selection of indicators based on analysts'

[5] OECD Glossary of Statistical Terms (last date of access: September 3, 2019): https://stats.oecd.org/glossary/detail.asp?ID=6278

judgement can be hard to avoid, but the allocation of weights can be made with more objectivity. Introduction of data envelopment analysis (DEA) shed light into this area. Popularized by Charnes et al. (1978), the DEA approach has been prevailingly applied as an operational tool to measure performance or efficiency of homogeneous entities with various weighted sum of outputs over weighted sum of inputs. The most advantageous feature of the DEA approach is that the weights can be adopted endogenously by the entities in favor of reaching their best performance or highest efficiency. In this way, the subjectivity due to manmade decisions can be prevented (Cherchye et al. (2004 & 2007)). The first implementation of DEA in the CI area was delivered by Melyn and Moesen (1991) to gauge macroeconomic performance. They realized that the advantageous feature of DEA can be used to tackle the flaw in constructing the CI system. Thereafter approaches containing DEA feature have been gradually used in many papers in CI aggregating and weight assigning process. The approaches are called DEA-like model.

The DEA-like model, also known as benefit of the doubt method, linearly aggregates all the indicators, each of which is multiplied by an endogenously chosen weight. With this model, the weights are allowed "to vary across objectives, over countries and through time" (Lovell, et al., 1995, page 508). Cherchye et al. (2007) thoroughly introduced the benefit of the doubt method step-by-step, henceforth, it is adopted by many researchers in their work, such as Zhou et al. (2007), Hatefi and Torabi (2010), Rogge (2012), Zhang, et al. (2013), Athanassoglou (2016), etc..

There are several papers that integrate the DEA-like model into the risk assessment of the COSC, on both supply stage and transportation stage. In Zhang et al.'s paper (2013), a systematic analytical CI approach is provided to measure the main risk factors that influence the oil import security of the whole upstream oil supply chain during different periods of time. On the supply stage, the supply risk is measured by the availability and accessibility of external oil suppliers. Under this concept, quantity of crudes resources available and distribution of such resources are quantified as two specific indicators: ratio of oil imports to world total oil imports and geopolitical oil supply market concentration, respectively. Concerning evaluating risks in transportation, Zhang et al. (2013) provided "trade route risk" as an indicator in their work. When introducing the trade route risk, the authors took three assumptions into consideration: 1) the larger amount of crudes carried on a certain route, the larger the risks, 2) the longer the distance of a certain route, the larger the risks, and 3) the greater insecurity of a chokepoint on route, the larger the risks. Then the authors calculated the trade route risk indicators through a formulation, which incorporates share of imports and distance from a certain region, and "military in politics" index. Thereafter, a two-phase DEA-like model, which is based on 'varying-common' weighs, was built to evaluate security of the crude oil import supply chain. The authors applied this method to determine the weights of each risk factor, in order to identify the main risk factors that influence the oil import security of the whole oil supply chain during different periods of time. To demonstrate the model, the authors conducted a case study on China, data ranging from 1993 to 2011. They found that risk factors presented a phase-transitioning characteristic, indicating that the main risk factors change from time to time while influencing China's oil import supply chain security. According to the authors, the evolution of the main risk factors can be classified into four time-phases, and in each phase, there is a dominant risk factor that weighs more than others. For example, in the first phase when China started to import more crude oil than export, from 1992 to 2002, due to lack of supplier diversification, the risk of concentrated import sources is more dominant than other risk factors. During the second phase of 2003 to 2007, China grew increasingly dependent on the imports of crude oil. Hence, high oil import dependence became the main risk. The third phase was right on 2008 when the financial crisis caused volatile oil price oscillation, which was the major risk at that time. Fourth phase was from 2009 to 2011, when some original net exporters transformed to net importers, and thus China faced the major risk of less choice of oil suppliers. During that period, the lack of external supply dominated all other risks (Zhang, et al., 2013).

Another analysis on quantifying oil import risks from oil suppliers and from transportation was proposed by Sun et al. (2014). The authors implemented the DEA-like method to weigh risk factors, too. The total risk is the sum of weighted country risks and weighted transportation risks, with the weights determined by a DEA-like model similar to Zhang et al.'s (2013). Their novelty is that they quantified the relationship between China's oil import risks and oil import costs, while others did not consider financial matters. This is achieved by applying a multi-linear regression approach. By doing so, the relationship between China's oil importing risks and oil importing costs is mapped out.

In a recent study on evaluation of crude oil supply security in South Asian countries, Mohsin et al. (2018) quantitively assessed risks that disrupt oil imports by creating a risk CI system. The authors sorted risks into supply risk, infrastructure risk, market risk, transportation risk, and dependence risk. Under each category, risk indicators, such as market liquidity, oil price volatility and so on, were given. According to the authors, there are two main methods to allocate weights to the risk indicators. One of the two methods is the aforementioned Multi-Criteria Decision Analysis (MCDA), and the other one is data envelopment analysis (DEA). In this paper, the authors argued that MCDA relies heavily on opinions from experts, which however can be prejudiced and unreliable. For this reason, the authors chose to use the DEA-like model to generate weights for the indicators. The DEA-like model used in this paper is slightly different than that in the previous two papers. In this paper, the authors took not only the “best” set of weights for the risk indicators, but also the model to compute the “worst” set of weights was presented. Contrary to the “best” set of weights, the “worst” set of weights “attempts to measure how close the entity evaluated is from the worst practice entity under the worst possible weights”, as explained by Zhou, et al. (2010, page 173). After that, Mohsin et al. (2018) combined the two models (models for the “best” and the “worst” sets of weights) into one overall index, to avoid partial evaluation of either the “best” or the “worst”. This DEA-based CI system allowed the authors to combine all individual risk indicators in a reasonable index and made it fair to compare the oil supply risk among different South Asian countries (Mohsin, et al., 2018).

Apart from integrating the DEA into CI, the model of diversification-imbedded CI was utilized by scholars to measure risks, mostly on the supply stage. Wu et al. (2009) stated that “diversification is one common indicator to measure risk caused by possible disruptions to energy imports to assess energy import security” (Wu, et al., 2009, page 3560). Yang et al. (2014) suggested that they quantitively modeled the external oil supply risks from the aspect of diversification of crude oil suppliers, using the Hirschman-Herfindahl index (HHI). The HHI, which is a tool developed to model market concentration originally, has become handful in gauging the concentration level of suppliers in the energy sector (Yang, et al., 2014). The authors modified the traditional HHI by considering country risks and potential export of various oil supplier countries, and by incorporating oil import dependency of importers to provide a more comprehensive understanding of the external oil supply risk index. By comparing the results of the indices of four main oil importing countries and regions (China, Japan, the US, and the European Union), the authors conducted a thorough empirical analysis on those countries' oil importing policies, following the suggestion of increasing strategic oil reserves to mitigate risks was given.

In another paper, Sun et al. (2017) introduced a framework based on four factors, namely 4A factors, that affect China's crude oil supply chain when it comes to imports. The 4A factors are availability of suppliers, accessibility of transportation, acceptability of the importer's infrastructure and affordability of the importer's economy. Risks of the first three factors are classified as internal disruption risks, while risk of the last factor is defined as external. Within the framework, each risk factor is comprised of several indicators, and a two-dimensional risk composite index is built upon the risk factors to present the overall systemic risk. The two dimensions refer to internal disruption risk (the first three factors of 4A) and external disruption risk (the last one of 4A). Following the models, an empirical analysis was applied to China's oil supply chain for the detailed situations in various periods of time. The authors found that the risk factors which dominate and impact the oil supply chain security vary over time, due to different policy focus at each time phase. They also found that Chinese companies transport their purchase mainly by sea, and the transportation routes heavily depend on a single chokepoint, that is the Malacca Strait. It reflects a high level of risk in transportation, due to the frequent activities of piracy in this area.

On the basis of the literature review we have conducted, methodology of a DEA-like model based Composite Indicator approach will be applied in our paper, in order to assess the risks among different oil suppliers in the crude oil supply chain of the refineries.

3. Methodology

In this part, we are going to build a Composite Indicators (CI) system, along with application of a DEA-like method, to assess how each risk indicator affects the stages of the crude oil import supply chain. The CI system has gradually been employed as a handy tool when decision makers need to compare multiple indicators at the same time for multiple entities. According to the OEDC guidebook (2008) and the steps suggested to construct a CI system, we will first identify the risk indicators that impact the crude oil import supply chain. Next, a normalization method will be selected based on comparison of three normalization methods. Lastly, an aggregation method, which is the model bearing characteristics of DEA, is presented.

3.1 Risk Indicators Identification

Risks in the crude oil import supply chain may impair energy security of a country or a company. The energy security is traditionally defined as the availability "to assure adequate, reliable supplies of energy at reasonable prices" (Yergin, 1988, page 111), and hence, "an uninterrupted energy supply is crucial" (Shin, et al., 2013, page 73). The interruptions could be derived from the risks of instability of supplier countries and disruption along the transport route. Each risk has its own features and needs to be investigated carefully.

In this part, risks that arise in the crude oil import supply chain are identified and indicators of each risk are explained in detail. As discussed earlier, risks may occur on each stage of the crude oil import supply chain, from supplier to transportation. Thus, the risk indicators will be demonstrated in this order accordingly.

3.1.1 Supply Stage

On the supply stage, risks of supply failure can be attributable to many reasons. Political or economic instability of a supplier country directly affects the supply of crude oil. For decades, countries in the Middle East are the major exporters in global crude oil trade. However, wars and political unrest in that area have exceedingly shaken the global crude oil market and caused two oil crises, which greatly impacted each and every player in the market, causing a sudden surge in oil prices due to short supply. Another example is Angola, whose political and economic development was disrupted by its 27-year civil war, potentially leaving its importers with instability of continuous supply. Iran and Venezuela, ranking number 7th and 11th in global crude oil export in 2016, are facing sanctions from the United States against their whole countries. In addition, policy alternation provides another possibility of uncertainty. In 2015, the United States lifted its export ban on crude oil, which became effective from four decades ago. Whether the United States will terminate its crude oil export again in the future remains a question. The indicator for political and economic risks of each country is as follows:

$$CR_{tj} = (PR_{tj} + ER_{tj})/2 \tag{1}$$

where CR_{tj} represents the country risk indicator of supplier j in year *t*; PR_{tj} is the political risk score of supplier j in year *t*; ER_{tj} is the economic risk score of supplier j in year *t*. The political and economic risk scores can be retrieved from various rating agencies, such as World Development Indicators of the Word Bank, International Country Risk Guide of the PRS Group, etc. Considering data availability and feasibility, we decide to choose scores from BMI Risk Reports as our data source. The scores from the BMI Risk Reports range from 1 to 100. The higher the scores means the higher level of security in political and economic aspects. Since the political scores and economic scores are given separately, we use the average of them to calculate an overall risk score.

Crude oil is regarded as non-renewable natural resource, indicating that the natural reserves of crude oil in an area is limited to a certain level in a relatively long-time span, unless there is breakthrough in exploration and prospecting technology. On the other hand, exploration and production can be determined by human decisions. Therefore, reserve-to-production (R/P) ratio is applied in measuring the remaining time length of possible crude oil production, given the amount of proved oil reserves and level of production. A higher R/P ratio signifies more sustainability in the crude oil supply, if production rate remains at the current level, without considering political or economic disturbance. Thereby, a country with a high R/P ratio is more likely to be an important supplier in the future. However, solely looking at this ratio can be biased, since not all of the production of a country will be exported, and some of the production will be retained for domestic consumption or national strategic reserves. To adjust the R/P ratio, share of export to production is combined with the R/P ratio to specify the export proportion of a supplier. Since a larger share of export in production implies that the supplier inclines to export more portion of the crudes produced. The indicator of potential oil exports is shown as below:

$$PE_{tj} = \frac{R_{tj}}{P_{tj}} \times \frac{EX_{tj}}{P_{tj}} \tag{2}$$

where PE_{tj} stands for the indicator of potential oil exports of supplier j in year t; R_{tj} and P_{tj} are the quantity of proved crude oil reserves and quantity of yearly production of supplier j in year t respectively; EX_{tj} denotes supplier j's annual export in year t. A bigger PE_{tj} indicates that the supplier remains certain ability in exporting crude oil in a longer time, rather than depleting the resource and thereafter terminating export. The reason of using export instead of net export, which is the total annual quantity of exports minus that of imports, is that in some countries, such as the US and Australia, they produce and export a great amount of crude oil with certain oil grades (with different density and sulfur content). However, in their domestic refineries, different grades of crude oil are needed other than the grades they produce in their own countries. Therefore, they import a large quantity of crude oil with different grades to feed their refineries, and sometimes the quantity of imports may be larger than that of exports. It results in a negative net export volume, and then a negative normalized indicator of potential oil export, leading to confusing results in the following analysis. Because the negative number in this situation does not mean the countries has no export ability, rather it indicates that the country requires other grades of crude oil in a large amount. Based on the consideration, we decide to employ only export quantity in this formula.

Dependency level of each supplier is used to evaluate to what extent an importer relies on the crude oil from a certain supplier. If the imports rely heavily on only one supplier or a small number of suppliers, when those suppliers cut off their supply, the importing countries would suffer from unexpected supply shortage, destructive impact on domestic production, and huge expense for finding substitute suppliers. The share of imports from each supplier to the total imports can be used to measure the dependency level of each supplier. It is formulated as:

$$DS_{itj} = s_{itj} = \frac{IM_{itj}}{TIM_{it}} \tag{3}$$

where DS_{itj} is the importer i's dependency level of supplier j in year t; s_{itj} is the share of country i's imports from supplier j in year t (IM_{tj}) to its total imports in year t (TIM_{it}). DS_{tj} ranges from zero to one, with the higher value meaning a more concentrated supplier selection, or too much dependency on this single supplier and less flexibility to cope with sudden disruptions.

3.1.2 Transportation Stage

Crude oil can be transported via crude oil tankers, pipelines, rail system and trucks. In 2015, 61% of total crude oil worldwide were transported by tankers, according to the U.S. Energy Information Administration (EIA)[6]. Pipelines can transport crudes in international oil trades; however, the trade parties have to be adjacent or geographically close to each other. Moreover, once a pipeline network is built, it is unlikely to change due to high expense and complexity of rebuild. Rail shares the same characteristic. And trucks, although they have more flexibility, long-distance travel is challenging due to safety considerations. Usually, when choosing crude oil transport mode in cross-ocean trades, marine transportation is always the top priority. Thus, in this study, only maritime transportation will be discussed.

In the maritime transportation of crude oil, an oil tanker is loaded at the supplier country's port, starting its voyage of tanks laden with crude oil and sailing through chokepoints, and finally it arrives at the discharging port. The time spent en route lasts from a few days to two months, depending on choice of routes, distance between loading and unloading ports, disrupting factors such as piracy attacks or bad weather. Assumption of one loading port and one discharging port in a single voyage is taken into consideration. A route in this paper is defined as the path that an oil tanker takes when it is loaded in a supplier region and then travels to the region where the discharging port is located. Its way to the next loading port is not included in the route.

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[6] U.S. Energy Information Administration: World Oil Transit Chokepoints (last visit on July 10, 2019) https://www.eia.gov/beta/international/regions-topics.php?RegionTopicID=WOTC

Crude oil suppliers are clustered in the Middle East, Northern Europe, North America, north-eastern part of South America, West Africa, North Africa and the Mediterranean. Routes of oil tankers start from those areas to the rest of the world. Length of the routes varies significantly. As Zhang et al. (2013, page 89) suggested, "the longer the distance, the greater the uncertainty and potential risks". Based on this concept, a multiplier of the distance of a route is calculated as:

$$MulL_{rj} = \frac{L_{rj}}{L_{min}} \tag{4}$$

where $MulL_r$ is a multiplier of the distance from supplier j on route r; L_{rj} is the distance from supplier j on route r; L_{min} is the distance of the shortest route. The multiplier ascends with longer distance of a route, so does uncertainty on that route. Although it can reflect some level of potential risks, it does not suffice to say that all risk factors en route have been considered.

On every day, heavy traffic flows through chokepoints, which are often narrow straits or canals close to the major crude oil producers and on the way of main seaborne transportation routes, rendering the chokepoints crucial positions in crude oil transportation. A crude oil tanker may sail through one or more chokepoints on its route to destination. Dependency of each chokepoint helps an importer to evaluate potential risk if the chokepoint faces any disturbance, for example shut-down. The dependency of each chokepoint can be depicted as:

$$DC_{ct} = \frac{IM_{ict}}{TIM_{it}} \tag{5}$$

where DC_{ct} is the dependency of chokepoint c in year t of importing country i; IM_{ict} is annual quantity of imports passing through chokepoint c from all routes, since different routes may share same chokepoints; TIM_{it} is total imports of country i in year t.

In a similar manner, dependency of each route is measured as:

$$DC_{rt} = \frac{IM_{irt}}{TIM_{it}} \tag{6}$$

where DC_{rt} indicates the dependency of route r in year t; IM_{irt} is annual quantity of import on route r. More amount carried on the same route reflects that the disruptions on this route will have a more significant impact to the importer than on other routes.

Piracy attacks en route are another factor that should be reckoned with. According to International Maritime Bureau (IMB), in 2015 there were 246 incidents of piracy attacks, within which 20 incidents happened to crude oil tankers[7]. Although the overall number of incidents is small compared to the worldwide traffic flow of oil tankers, once it happened, the loss can be huge. Loss includes but is not limited to theft of cargo and other properties, damage of onboard equipment, violence towards crew, and so on. Based on the reports of IMB from 2015 to 2018, we are able to conclude that the piracy active areas highly coincide with the chokepoints and oil transportation routes. Hence, piracy attacks and armed robberies should be considered as an indicator. Sun et al. (2017) proposed a formulation to estimate the probability of piracy attacks in a select route that can be referred to in this research:

$$P_{rt} = \sum_{c=1}^{n} p_{crt} \prod_{\substack{k=1 \\ k \neq c}}^{n} (1 - p_{krt}) \tag{7}$$

where P_{rt} is the probability of piracy attacks of route r in year t; n denotes the set of chokepoint nodes; k is the chokepoint other than c on the selected route r; while p_{crt} and p_{krt} are the probabilities of piracy attacks at chokepoint c and k on the route r in year t, respectively; $(1 - p_{krt})$ is the probability of passing a chokepoint safely.

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[7] International Maritime Bureau Piracy Report (last visit on July 10, 2019): https://www.icc-ccs.org/piracy-reporting-centre

For the importers, especially for some medium-sized oil companies or independent refineries, owning and maintaining an oil tanker fleet can be cost consuming. It is much more efficient for them to lease a spot-chartered tanker in order to meet one-time demands, after a purchase of crude oil is made. The oil buyer signs a leasing contract with a shipping company, which is often a third-party company. The two parties usually will negotiate a freight rate based on the flat rate table provided by Worldscale, who renews and publishes a new set of rate table for reference each year. The rate table contains fixed flat rates of port pairs, including one loading port to one unloading port, or multiple ports on each side. The Worldscale is a point-of-scale system, and the flat rate per ton values 100 points. Based on tanker sizes and different routes, the oil buyer and shipping company may negotiate another point scale, which is established in terms of a percentage of the flat rate. By multiplying the negotiated point scale to the flat rate per ton, two parties obtain the freight rate per ton of their shipment. Although buyers and shipowners agree upon a rate at will, for realistic purpose, they usually refer to a weekly renewed market average rate published by S&P Global Platts according to fluctuating market conditions, considering various tanker sizes and routes of paired regions. The Platt's freight rate is the equivalent US dollar per metric tonne freight rates based on a basket of Worldscale flat rates. Volatility of shifting spot-chartered tanker freight rate can be magnified by the enormous amount of cargo on an oil tanker. Therefore, the volatility of tanker freight rate is an important indicator for the buyers to look at. It can be expressed as below:

$$VFR_{rtz} = \frac{1}{W-1} \sum_{\omega=1}^{W-1} (\log(\frac{FR_{rtz,\omega+1}}{FR_{rtz,\omega}}))^2 \quad (8)$$

where VFR_{rtz} is the indicator of volatility of freight rate in year t, on route r of tanker size z; W is the number of total weeks that Platt's freight rate is published in year t; $FR_{rtz,\omega}$ the freight rate published on week ω in year t on route r of tanker size z. This indicator is in a variant version of the first difference of log, which is often used to measure the percentage of change in prices fluctuations. Then the first difference of log is applied by several studies on measuring the volatility of monthly price changes of crude oil (Merton (1980), Andersen, et al. (2003), and Park and Ratti (2008)). We believe that the volatility of monthly price changes and the volatility of weekly freight rate changes share similarities in nature, such that both of them oscillate due to the impact of demand-supply relation on the market. Thus, the formula is adopted as an indicator.

Risk of encountering extreme weather and delays is difficult to quantify. However, it greatly impacts the traveling time of tankers, therefore massive delay en route due to bad weather conditions could result in significant demurrage fee for the importers. Thus, it could be a valuable problem and provide a future study direction for whom are interested.

In this paper, we assume that the supplier countries and routes share the relation of one-to-one correspondence. Specifically, given a pair of supplying and importing countries, there is only one route connecting the two countries for maritime transportation. In reality, the situation can be much more complex in that marine routes between countries are provided by port pairs. It indicates that if a country stretches over a continent, for example Canada, ships from ports on different sides of the country may sail via different routes to a same destination country. Considering pairs of ports greatly complicates the problem and requires massive amount of data which can be challenging at this moment. Thereupon, the assumption of one country pair, one route is made. Based on the assumption and from an importing country's point of view, its suppliers can be categorized by their routes. Accordingly, the suppliers sharing the same route obtain homogenous indicators on the transportation stage. Thus, the comparison and ranking will be entailed among routes rather than suppliers on the transportation stage. However, when comparing risks of supplier countries which belong to different route categories, the set of indicators on the transportation stage should be taken into account.

3.2 Normalization Method

A normalization method is required before aggregating the individual indicators. Since the indicators have different measurement units, normalization of the indicators is a way to convert them into dimensionless vectors that can be compared with each other. In our problem, the indicators have different orders of magnitude, the indicators with a larger order of magnitude will dominate the others and then lead to an unfair comparison. Moreover, during the weights assigning process when applying the DEA-like model, although the overall score will not be affected by the units of measurement, the weights depend on the units. Thus, without normalization, if one adds restrictions on the weights, the meaning embedded in the restrictions may be ambiguous and hard to be recognized (Cherchye, et al., 2007). To overcome this issue, Cherchye et al. (2007) suggest that preliminary normalization should be applied to the original indicators.

The normalization methods can be classified into linear scale, ratio scale and ordinal. We have compared three most commonly used methods: Min-Max normalization, Z-score normalization, and "distance-to-the-group-leader" normalization. The first two methods belong to linear scale category, and the last one is a ratio scale method.

The Min-Max normalization is a linear transformation of original data and turns the original data into [0,1], meaning that the maximum value in the original data set is normalized to one, and the minimum value is transformed to zero. The Min-Max normalization is formulated as:

$$X_\gamma^* = \frac{x_\gamma - \min_{\varrho\in\Gamma}(x_\varrho)}{\max_{\varrho\in\Gamma}(x_\varrho) - \min_{\varrho\in\Gamma}(x_\varrho)} \tag{9}$$

where X_γ^* is the normalized version of γth indicator; x_γ is the γth original indicator; $\min_{\varrho\in\Gamma}(x_\varrho)$ and $\max_{\varrho\in\Gamma}(x_\varrho)$ are the minimum and maximum value of indicators in the set Γ. After processing the indicators using Min-Max normalization, the indicators share the exact same scale, and the relations within original data have been kept. It is rather easy to interpret and understand as well. The flaw of this method is that it could not handle outliers so well. When new data is added and becomes the new minimum or maximum value, which exceeds the one in the original set of data, then the new minimum or maximum value need to be redefined, otherwise an error will occur. Also, if a set of data is centralized with some extremely high numbers, the normalization will generate values close to zero and there would be mere significant difference among the values.

The Z-score normalization processes the data based on their mean and standard deviation. The processed data follows Normal distribution with mean of zero and standard deviation of one. The formula of Z-score normalization is as below:

$$X_\gamma^* = \frac{x_\gamma - \mu_\Gamma(x_\gamma)}{\sigma_\Gamma(x_\gamma)} \tag{10}$$

where $\mu_\Gamma(x_\gamma)$ is the mean of all x_γ, and $\sigma_\Gamma(x_\gamma)$ is the standard deviation of all x_γ. Compared with the Min-Max normalization, the Z-score method is suitable for the situation where the maximum or minimum value is unknown. It also performs better on the outliers than the Min-Max normalization method. However, the processed data in this method do not share the same scale. The processed data show positive numbers when their original values are above the original mean, and present negative numbers conversely. Furthermore, Z-score method performs better with normally distributed data.

The distance-to-the-group-leader normalization is employed by Zhou et al. (2006) and Cherchye et al. (2004). It is expressed as:

$$X_\gamma^* = \begin{cases} \dfrac{x_\gamma}{\max\limits_{\varrho\in\Gamma}(x_\varrho)}, \text{(for } x_\gamma \text{ that is the larger the better)} \\ \dfrac{\min\limits_{\varrho\in\Gamma}(x_\varrho)}{x_\gamma}, \text{(for } x_\gamma \text{ that is the smaller the better)} \end{cases} \tag{11}$$

where $\frac{x_\gamma}{\max\limits_{\varrho\in\Gamma}(x_\varrho)}$ transforms the indicators that are considered as the lager the better, and the maximum value is regarded as the group leader with a value of one after normalization; while $\frac{\min\limits_{\varrho\in\Gamma}(x_\varrho)}{x_\gamma}$ is used for those indicators that are the smaller the better, and the best indicator with the minimum value will be transformed to one. As a ratio-scale normalization method, it preserves the unit-invariance of the original indicators, and thus the inherent meaning does not vanish after conversion (Cherchye, et al., 2004). The normalized indicators under this transformation method stay in a range of (0,1]. Compared with the range in the Min-Max normalization, this method naturally avoids any indicator to be converted to zero due to computation. However, in the Min-Max normalization, the transformed indicators are not necessarily the larger the better, while in the distance-to-the-group-leader normalization the X_γ^* is measured as better when its value ascends. Therefore, one should take caution choosing the indicators in respect of their moving directions.

Under the context of our problem, in the DEA-like model, conditions will be imposed to the weights. As we stated before, the weights depend on measurement units due to the endogeneity inherited from the indicators. Hence, any substitution of the original indicators in the normalization process may impair this feature. On the other hand, the ratio-scale method "will lead to exactly the same outcome as when using the original data", as suggested by Cherchye et al. (2007, page 122). Consequently, the distance-to-the-group-leader normalization is selected.

For the indicators on the supply stage, the normalization is expressed as:

$$X^*_{\gamma,tj} = \begin{cases} \dfrac{x_{\gamma,tj}}{\max\limits_{j\in J}(x_{\gamma,tj})} \\ \dfrac{\min\limits_{j\in J}(x_{\gamma,tj})}{x_{\gamma},tj} \end{cases} \tag{12}$$

where $x_{\gamma,tj}$ is the original γth indicator of supplier j in year t; $\max\limits_{j\in J}(x_{\gamma,tj})$ is the maximum value of the original γth indicator among all suppliers from set J in year t; $\min\limits_{j\in J}(x_{\gamma,tj})$ shares the same interpretation as $\max\limits_{j\in J}(x_{\gamma,tj})$.

For the indicators on the transportation stage, the normalization is expressed as:

$$Y^*_{\gamma,rt} = \begin{cases} \dfrac{y_{\gamma,rt}}{\max\limits_{r\in R}(y_{\gamma,rt})} \\ \dfrac{\min\limits_{r\in R}(y_{\gamma,rt})}{y_{\gamma},rt} \end{cases} \tag{13}$$

where $y_{\gamma,rt}$ is the original γth indicator of route r in year t; $\max\limits_{r\in R}(y_{\gamma,rt})$ is the maximum value of the original γth indicator among all routes in set R in year t; $\min\limits_{r\in R}(y_{\gamma,rt})$ retains the same interpretation as $\max\limits_{r\in R}(y_{\gamma,rt})$.

Since the normalization process of both supplier and transportation stage will lead the normalized results to a direction of the larger the better, as well as the outcome of the following DEA-like model, the risk indicators will be processed and deemed in an inverted way as safety indicators. Because the purpose of this study is risk analysis, the inversion will be treated only for the intention of computation. For example, before normalization, the larger the probability of piracy attacks on a given route, the riskier the route is; after normalization, the larger the indicator, the safer the route is. Although seems somehow twisting, the normalization does not change the inherent meaning of the indicators. Since if we take the reciprocal of the indicator at the first place, for instance the piracy attack probability, and set it as the larger the indicator, the smaller the chance of being attacked, after normalization the indicator shows the same result as in the first situation. More details of inversion of indicators can be found in the Table 3.2-1:

Table 3.2- 1 Details of inversion of indicators

Indicators	Direction before normalization	Direction after normalization
Political and economic risk of a supplier country	The larger the better	The larger the better
Potential oil export	The larger the better	The larger the better
Dependency on each supplier	The smaller the better	The larger the better
Multiplier of distance of a route	The smaller the better	The larger the better
Dependency of each route	The smaller the better	The larger the better
Probability of piracy attacks in a selected route	The smaller the better	The larger the better
Volatility of freight rate	The smaller the better	The larger the better

3.3 DEA-like Model

As we have discussed in the literature review part, the Composite Indicator (CI) approach is deemed as contraversial, because the weights of indicators within a CI are determined by experts whose opinions are based on their own subjectivity and thus could be biased. To overcome the subjectivity of the CI approach, introduction of the data envelopment analysis (DEA) helps to alleviate the impact of the opinions of experts. The endogeneously generated weights of indicators by the DEA approach can assign the most favorable sets of weights to the indicators of an entity, in order to let the entity reach its best performance. Although the entity is at its best performance level with the DEA-chosen weights, performance of different entities are at various levels, and thus, comparison among entities can be made fairly. The concept of DEA is incorporated in the CI, and it is renamed as DEA-like model, or benefit of the doubt method. This method is thoroughly demonstrated by Cherchye et al. (2007), and models proposed in their paper are widely adopted by many researchers in their work, such as Zhou et al. (2007), Hatefi and Torabi (2010), Rogge (2012), Zhang, et al. (2013), Athanassoglou (2016), etc.. In Cherchye et al.'s work (2007), the model was designed to measure and compare the CI scores for countries on each indicator, which perfectly fits our situation in this paper. Thereby, the model presented by Cherchye et al. (2007) will be adopted in our paper to aggregate the indicators we discussed earlier.

The benefit-of-the-doubt model is established based on the concept of DEA, with different expression and meaning on both sides of the equation, compared with the traditional DEA formula. On the left hand side of the equation, instead of efficiency as traditionally measured, it is the Composite Indicator (CI) score of countries; while on the right hand side, it is expressed as the ratio of the maximization of a selected country's weighted-sum indicator to that of the benchmark among all studied countries. It is denoted as (Cherchye, et al., 2007):

$$CI_c = \max_{w_{c,\gamma}} \frac{\sum_{\gamma=1}^{\Gamma} w_{c,\gamma} x_{c,\gamma}}{\max_{\zeta \in \mathbb{C}} \sum_{\gamma=1}^{\Gamma} w_{c,\gamma} x_{\zeta,\gamma}} \tag{14}$$

where CI_c is the Composite Indicators score for country c; $w_{c,\gamma}$ is the most favorable weight for country c of its γth indicator; $x_{c,\gamma}$ is the value of γth indicator of country c; $\mathbb{C}$ is the set for all studied countries; ζ is a country from set $\mathbb{C}$.

Due to the fact that the benchmark can always perform better than the others, allowing its maximal CI value to be one. Then the whole input part transforms to a "dummy input" of 1 for all countries. Consequently, formulation (14) can be linearized into the form of formulation (15) (Cherchye, et al., 2007):

$$CI_c = \max_{w_{c,\gamma}} \sum_{\gamma=1}^{\Gamma} w_{c,\gamma} x_{c,\gamma} \tag{15}$$

Subject to:

$$\sum_{\gamma=1}^{\Gamma} w_{c,\gamma} x_{c,\gamma} \leq 1, \quad for\ each\ country\ c \tag{16}$$

$$w_{c,\gamma} \geq 0, \quad for\ each\ indicator\ \gamma \tag{17}$$

$$\alpha_\gamma \leq \frac{w_{c,\gamma} x_{c,\gamma}}{\sum_{\gamma=1}^{\Gamma} w_{c,\gamma} x_{\mathbb{C},\gamma}} \leq \beta_\gamma, \quad for\ each\ indicator\ \gamma \tag{18}$$

Constraint (16) regulates that the CI value for any country c cannot be greater than one, based on the meaning of "ratio" mentioned earlier. Constraint (17) is a non-negativity constraint, ensuring that no indicators will be weighted to a negative number that will impair the realistic meaning of the whole CI score. Accordingly, the overall CI score for each country c is restricted to [0,1]. Constraint (18) is a proportional indicator share restriction propounded by Wong and Beasly (1990). This restriction enforces each weighted indicator to fall within a range of proportion of the whole CI score, so that the share of each weighted indicator to the sum of all weighted indicators can be limited to a reasonable range. The lower bound α_γ should be a small enough number to make sure that no indicator will be ignored due to the favorable choice of weights; and the upper bound β_γ prevents an indicator to dominate too much. However, the bounds are not easy to be determined with full objectivity. There is possibility that either or both of the bounds can be binding, where the country can perform better when the binding bound is more relaxed (Cherchye, et al., 2007). Thus, in our case, we will firstly employ no restrictions on the indicator shares and observe the results when all weights are chosen with full flexibility. After that, we will apply different levels of bounds to observe to how do the indicators' performance change, when the upper and lower bounds gradually shift.

A summary of all the models and formulations can be found in the Appendix A, for readers' reference. In the next part, a case study on the risk analysis of Chinese refineries' crude oil importing supply chain will be discussed.

4. Case Study

In this section, a case study on risk analysis of Chinese refineries' crude oil import supply chain is discussed in detail. First of all, data collection and pre-process are delineated. Then, based on the data obtained, a preliminary analysis on indicators is conducted. After that, the DEA-like model discussed in the last section will be applied to the case, with variant restrictions on the indicator shares. A four-sector analysis of CI scores and quantity of imports is exercised to provide a more comprehensive analysis on the crude oil import supply chain.

4.1 Data Collection

According to the indicators we listed in the methodology section, data required in composing indicators and source of data are summarized in Table 4.1-1.

In our study, data on China's crude oil imports from 2015 to 2018 was collected. Data shows that there were 55 suppliers in total exporting crudes to China during that period. By calculating each country's share of China's annual total import quantity, we found that in each year, approximately 95% of China's total import comes from around 60% of the suppliers. Each of the other 40% of suppliers contributes less than 0.5% in the annual total amount. Hence, to streamline the data, we decided to regard those data as non-significant and to omit the countries with less than 0.5% proportion in all four years. As a result, 24 countries remain in the analysis, most of which have a proportion above 0.5%, while only a few of them show a proportion below 0.5% in some of the four years. Specific number of countries with more than 0.5% proportion of imported crudes and their total percentage can be found in Table 4.1-2.

Table 4.1- 1 Data required for the case study and source of data

Stage	Indicators	Data Required	Source	Website (last visits on July 17th, 2019)
Supply stage	Political and economic risk of a supplier country	Political risk score and economic risk score	BMI Risk Reports (from Library of HEC Montréal)	https://proxy2.hec.ca:2379/publication/2044555/citation?accountid=11357
	Potential oil export indicator	Total proved reserve quantity of crude oil of suppliers	BP Statistical Review	https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html
		Annual extraction (production) of crude oil of suppliers	Same as above	
		Annual export and import quantity of suppliers	UN Comtrade Database OPEC Annual Statistical Bulletin	https://comtrade.un.org/ https://www.opec.org/opec_web/en/publications/202.htm
	Dependency on each supplier, based on the import volume	Annual import quantity from each supplier of China	International Trade Center	http://www.trademap.org/Country_SelProduct_TS.aspx
Transportation Stage	Multiplier of distance of a route	Distance from crude oil port in supplier countries to Qingdao port, China	Sea Distance	https://sea-distances.org/
	Dependency of each chokepoint	Traffic flow of Chinese import crude oil tankers passing via each chokepoint	Estimated based on traffic flow data from General Administration of Customs of China	http://english.customs.gov.cn/statics/report/preliminary.html
	Dependency of each route	Traffic flow of Chinese import crude oil tankers passing via each route	Same as above	
	Probability of piracy attacks in a selected route	Number of piracy attack incidents	International Maritime Bureau (IMB)	https://www.icc-ccs.org/piracy-reporting-centre
	Volatility of freight rate	Weekly freight rate of spot-chartered oil tanker from each region to Qingdao port, China	S&P Global Platts	https://www.spglobal.com/platts/en

Table 4.1- 2 Number of supplier countries with share of imported crudes no less than 0.5%

Years	*2015*	*2016*	*2017*	*2018*
Number of countries with share larger than 0.5%	20	21	23	20
Total percentage of countries with share larger than 0.5%	94.93%	95.91%	95.03%	95.29%

More detailed data on the 24 suppliers and their shares in import can be found in Table B-1 in Appendix B. As indicated by footnotes under Table B-1, from 2015 to 2017, 15 million tonnes of crude oil imported from the Russian Federation were transported via pipeline per year. From 2018, the quantity of crude oil transported via pipeline raise to 30 million tonnes per year. In our study, the portion of oil import via pipeline should be deducted from the total amount. Also, all crude oil import from Kazakhstan are transported via pipeline, thus import from this country will not be considered in our study, since maritime transportation is our focus in this paper.

Therefore, further discussion will be based on the data of the 23 countries representing China's major suppliers of crude oil import. These 23 suppliers are categorized by their region of routes, that is the classification of the routes, rather than geographical locations of the supplier countries. The reception port in China is assumed to be Qingdao port, where it processes the largest amount of discharge of crude oil in China. More information on category, routes and distance from supplier port to Qingdao port can be found in Table 4.1-3 below. An illustration of geographical locations of supplier countries and routes is presented in Figure 4.1-1.

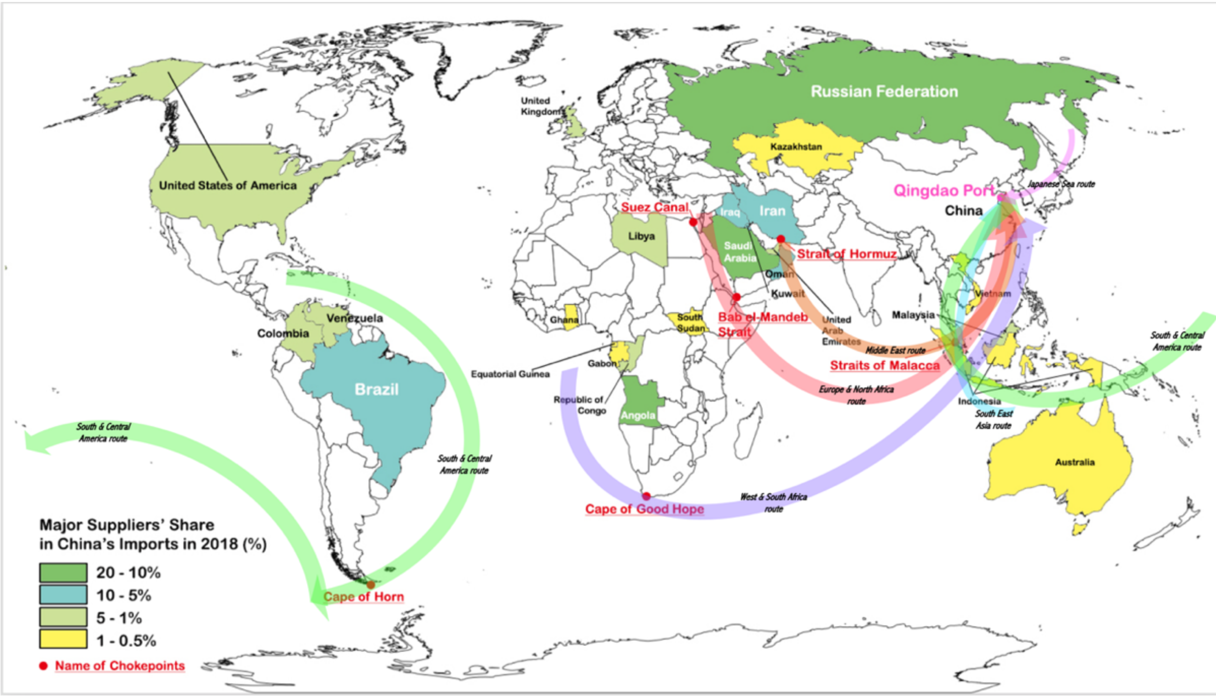
Table 4.1- 3 Category of Suppliers Based on Region of Routes

Region Based on Routes	Routes and Chokepoints	Supplier Countries	Distance between Supplier and Qingdao Port, China (nm)
Middle East	Hormuz Strait - Straits of Malacca - South China Sea	Iran, Islamic Republic of	6,198
		Iraq	6,358
		Kuwait	6,288
		Oman	5,609
		Saudi Arabia	6,164
		United Arab Emirates	6,004
South & Central America	North part of South America - Cape of Horn - Pacific Ocean - Straits of Malacca - South China Sea	Brazil	12,297
		Colombia	16,301
		United States of America	17,507
		Venezuela	15,545
Europe & North Africa	Suez Canal - Bab el-Mandeb Strait - Straits of Malacca - South China Sea	Libya	7,915
		South Sudan	6,741
		United Kingdom	11,017
West & South Africa	Cape of Good Hope - Straits of Malacca - South China Sea	Angola	9,683
		Congo, Republic of	9,727
		Equatorial Guinea	10,277
		Gabon	10,080
		Ghana	10,508
South East Asia & Pacific	Straits of Malacca - South China Sea	Australia	3,582
		Indonesia	2,660
		Malaysia	2,467
		Vietnam	1,963
Japanese Sea	Japanese Sea - East China Sea	Russian Federation	1,001

As shown in Table 4.1-3, although the United States (US) is a North American country, its largest crude oil exporting ports are located in the Gulf Coast, which is close to the South and Central (S&C) America. The location is close to Panama Canal, but oil tankers from the US share the route with other S&C American countries to China. The reason is that Panama Canal can only allow tankers of Panamax size or smaller tankers to traverse through, any other tankers with larger sizes have to detour via other routes. Common Panamax tankers have a tonnage limit of 52,500 deadweight tonnage (DWT) according to the Panama Canal Authority. However, the long distance from the US to China entails shipping crudes with tankers of Panamax or smaller vessel is uneconomical. Larger tankers such as VLCC (Very Large Crude Carrier) or ULCC (Ultra-Large Crude Carrier) are used for long distance journey. A VLCC typically refers to vessels carrying 160,000 to 320,000 DWT, while a ULCC can carry 320,000 DWT and above[8]. This situation also applies to the supplier countries in the Central America area. Therefore, oil tankers from the US will be considered to sail via the South and Central America route, which is to detour via the Cape of Horn on the far south edge of the South American continent. Another information on this route is that, when oil tankers sail across the Pacific Ocean and reach Asia, they have to stop by the Straits of Malacca in order to refuel before they go to China. This makes the Straits of Malacca an inevitable chokepoint on their route. Furthermore, crude oil exports from Russia to China usually use the port at Vladivostok, which is on the east side of the Russian territory. Tankers travel through the Japanese Sea and approach China from the north. It is the only route that avoids the Straits of Malacca.

[8] The deadweight tonnage of VLCC and ULCC are based on information from the U.S. Energy Information Administration (EIA): https://www.eia.gov/todayinenergy/detail.php?id=17991

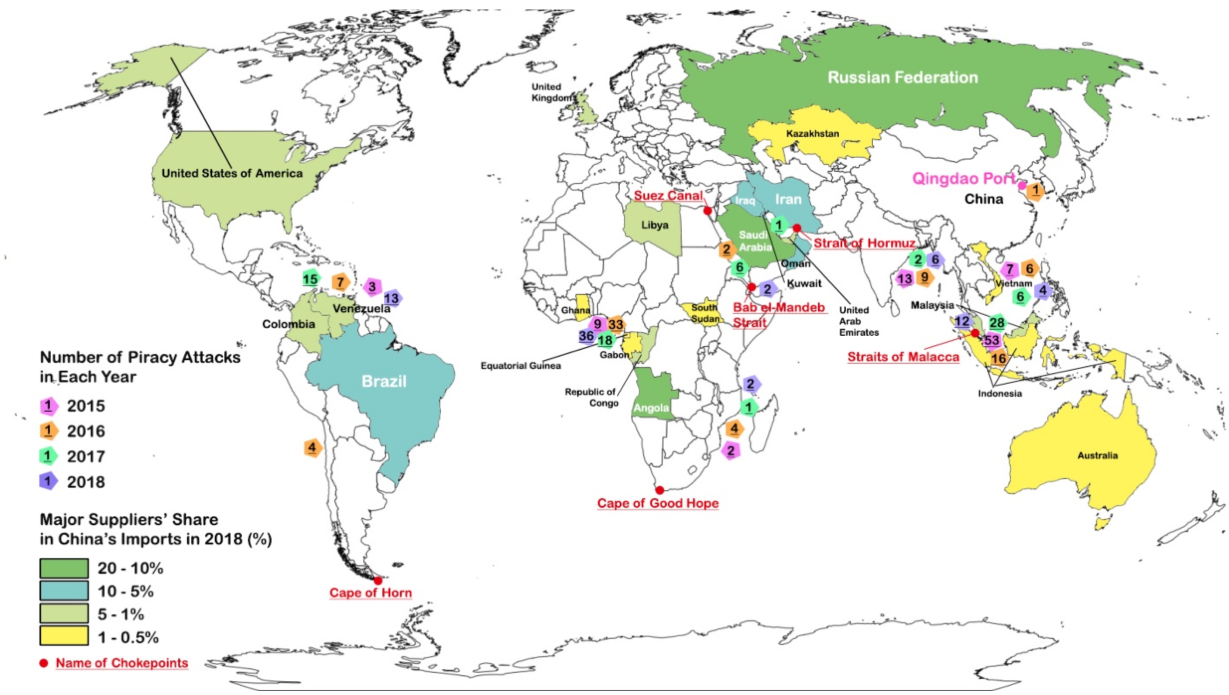
Figure 4.1- 1 Geographical locations of Supplier Countries and Routes



Traffic flow of Chinese import crude oil tankers passing via each chokepoint and via each route is estimated based on the trade flow data provided by the General Administration of Customs of China. We categorized the countries based on the routes listed above, and then added up all quantity of oil transported and number of ships on each route in each year. The traffic flow of a given chokepoint is calculated by summing up the quantity of imports on the routes that contain the given chokepoint. For example, five routes, excluding the Japanese Sea route, all pass via the Straits of Malacca, then the annual quantity of the five routes will be added together to generate the yearly quantity of cargo that traverse through the Straits of Malacca heading towards China. The number of ships sailing through each chokepoint is estimated in the same way. Since the indicators of chokepoints are generated from the data of routes, incorporating both of the dependency of chokepoints and the dependency of routes may cause overlap and redundancy. To prevent the overlap, we decided to only incorporate the dependency of each route in the DEA-like model. However, to analyze the dependency of each chokepoint can be quite helpful for the decision makers. Hence, this indicator will be discussed in the preliminary analysis.

Number of piracy attacks is extracted from reports of the International Maritime Bureau (IMB) from 2015 to 2018, and the numbers can be found in the Appendix B in Table B-2. We distinguished the attacks towards all tankers from other types of vessels. The reasons of including all types of tankers, rather than just oil tanker are as follows. First of all, after investigating the narratives of the incidents that happened on crude oil tankers and other types of tankers, we discovered that in most cases, the armed intruders intended to steal the private properties of the crew, rather than plundering the cargo. Therefore, the type of cargo on a tanker does not matter for the intruders, in most cases. Secondly, in a small but still considerable number of incidents, the robbers stole cargo or bunker oil from crude oil tankers as well as non-crude oil tankers. Based on the similar nature of cargo, being in the form of liquid, no differentiation is made among crude oil, fuel oil and other liquid chemical products, such as asphalt, in the case of piracy attacks. The numbers and locations of the attacks can be found in Figure 4.1-2. More details will be discussed in the preliminary analysis part.

Figure 4.1- 2 Geographical locations of Piracy Attack incidents from 2015 to 2018



Because the suppliers are classified according to the six routes in Table 4.1-3, the indicators on the transportation stage are calculated based on those routes too. Thereby, when a supplier country is in the same region as a given route, the transportation indicators can be assigned to each supplier country in that region. For instance, since oil tankers from Saudi Arabia take the Middle East route, transportation indicators of the Middle East region (except the distance multiplier which is estimated from port to port), such as dependency of each route, probability of piracy attacks and volatility of freight rate on each route, can be assigned to Saudi Arabia. In this sense, all the indicators are allocated on country basis, allowing the DEA-like model to be applied to all indicators of a country, without distinction between supply stage indicators and transportation stage indicators.

As introduced in section one and in the modelling section, 90% of crude oil imports are delivered by foreign tankers (Sun, et al., 2017). Chinese refineries have to lease tankers from spot-chartered tanker market. The spot-chartered rent rates are collected from S&P Global Platts on a weekly basis for all four years from 2015 to 2018. The upload areas are based on the six routes as in Table 4.1-3. The rates are tonnage-based instead of distance-based, since the length of distance has already been considered into the rates.

4.2 Preliminary Analysis

As we have explained in the modeling section, the country risk consists of the average value of political risk and economic risk, with a full score of 100 and descending order of grades, meaning the less risk score the worse performance. Due to data availability, we are only able to find risk reports for each supplier country in year 2017. However, the risk scores are given based on long-term prediction, so we decided to use the scores for the four-year analysis in our study. As can be found in Table 4.2-1, political and economic risk scores of each country are displayed. For all supplier countries, the average value of political risk score is 59.51, with a minimal value of 20.2 in Libya and a maximal value of 88.9 in United Kingdom. The average value of economic risk score is 56.47, with a minimal value of 38.2 in Venezuela and a maximal value of 75.7 in the United States of America. The average of both political and economic risk score has a mean of 57.99, a minimum of 30.8 in Libya and a maximum of 81.7 in United Kingdom.

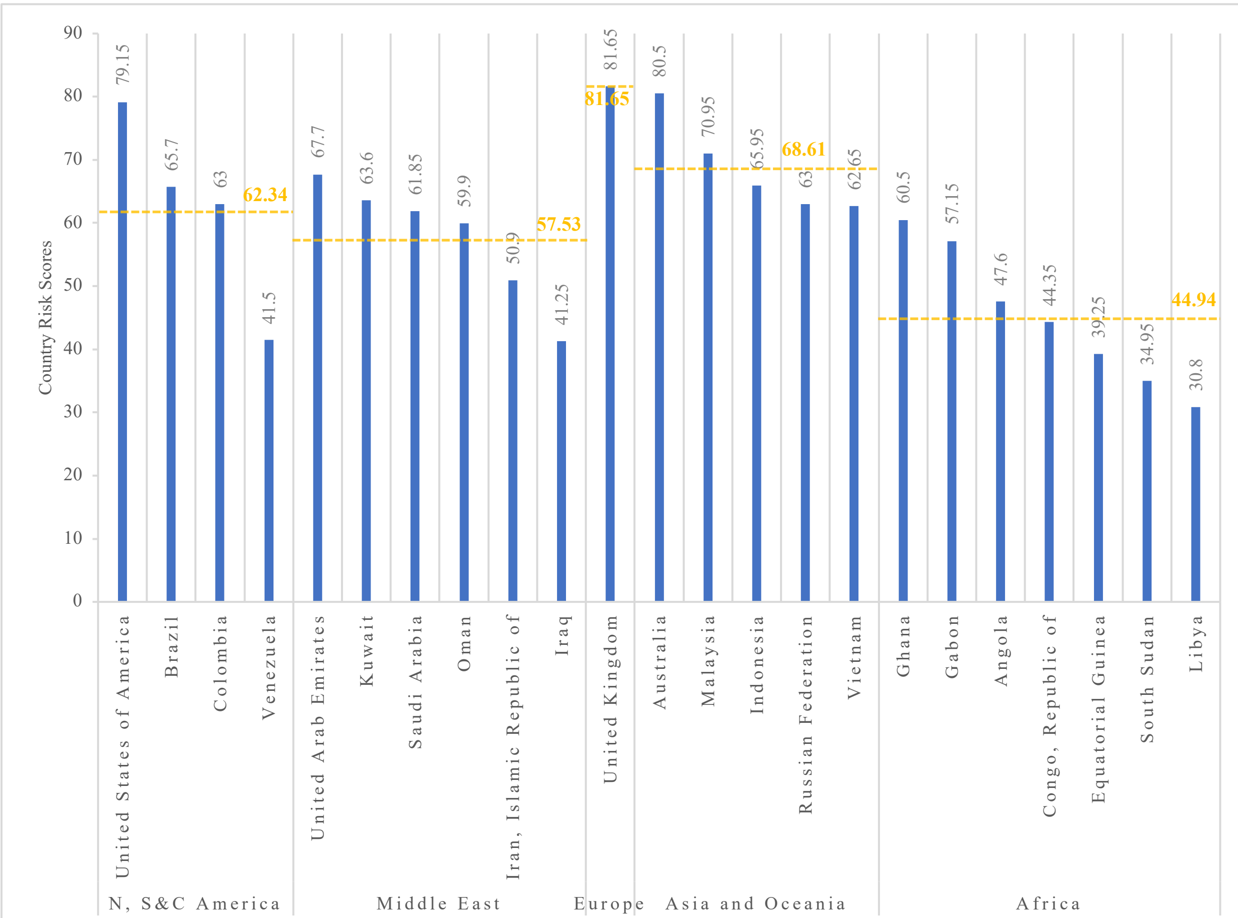
Table 4.2- 1 Political risk scores, economic risk scores and average of the two scores

Countries	***Political Risk***	***Economic Risk***	***Average of Political and economic risk***
Angola	52.1	43.1	47.6
Australia	88.4	72.6	80.5
Brazil	68.9	62.5	65.7
Colombia	62.4	63.6	63
Congo, Republic of	45.6	43.1	44.35
Equatorial Guinea	38.3	40.2	39.25
Gabon	63.1	51.2	57.15
Ghana	73.5	47.5	60.5
Indonesia	63.4	68.5	65.95
Iran, Islamic Republic of	54.0	47.8	50.9
Iraq	36.7	45.8	41.25
Kuwait	67.4	59.8	63.6
Libya	**20.2**	41.4	**30.8**
Malaysia	69.5	72.4	70.95
Oman	68.9	50.9	59.9
Russian Federation	61.7	64.3	63
Saudi Arabia	58.7	65.0	61.85
South Sudan	30.4	39.5	34.95
United Arab Emirates	69.6	65.8	67.7
United Kingdom	**88.9**	74.4	**81.65**
United States of America	82.6	**75.7**	79.15
Venezuela	44.8	**38.2**	41.5
Vietnam	59.7	65.6	62.65
Mean	59.51	56.47	57.99
Standard Deviation	17.54	12.71	14.37
Min	20.2	38.2	30.8
Max	88.9	75.7	81.7

Chart 4.2-1 shows the grouped country risk scores by regions of supplier countries. The dotted yellow lines are the average scores for each region group, and the yellow numbers are the average scores. From the chart, we can observe that Europe is the region with the highest average country score of 81.65, since UK is the only country in this group and it has the highest score among all suppliers. Asia and Oceania countries have the second highest score of 68.61, and within this group Australia is the upper bound with a score of 80.5 and Vietnam is the lower bound with a score of 62.65. North, South and Central America ranks number three among all regions, with an average score of 62.34. The USA has the highest score of 79.15 in this group and Venezuela has the lowest score of 41.5. The Middle East comes next, which has an average score of 57.53, where the United Arab Emirates contributes the highest score of 67.7 and Iraq shares the lowest score of 41.25.

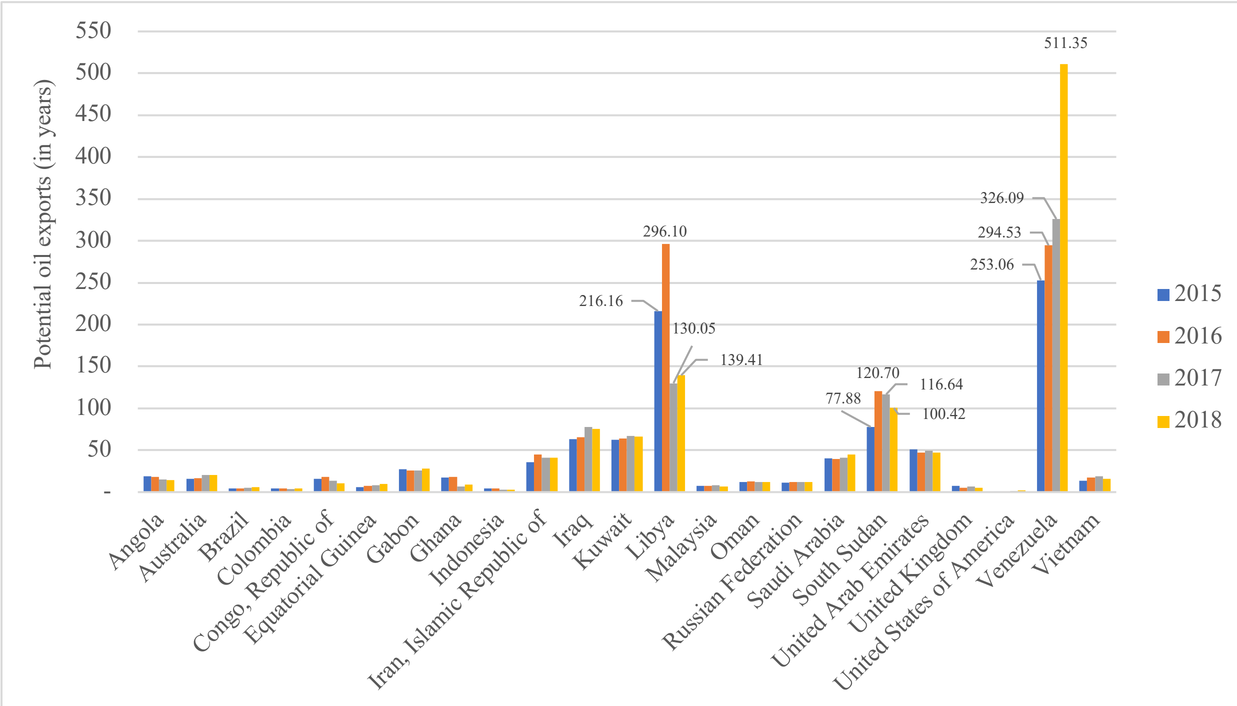
Africa countries have the lowest average score of 44.94, where Ghana's score is the highest, which is 60.5, and Libya's is the lowest, which is 30.8.

Chart 4.2- 1 Country risk scores by regions



As already mentioned in the modeling section, the potential oil exports level is measured in years of sustainable crude oil supply, based on the production and exportation level at the time of measurement. This indicator incorporates amount of proved oil reserve, annual production quantity and annual export quantity. After processing the data, Chart 4.2-2 is presented as follows:

Chart 4.2- 2 Potential oil export level of supplier countries from 2015 to 2018



In the chart, the potential oil export level of most countries is stable across four years, except Libya, South Sudan and Venezuela. Libya had a highest level of 296.1 years of crude oil exports in 2016, then the value dropped to 130.05 in 2017 and 139.41 years in 2018. It is because the annual production of Libya increased from 20.5 and 19.3 million tonnes in 2015 and 2016 to 43.8 and 47.5 million tonnes in 2017 and 2018 respectively. Along with the surge in oil production in Libya, its annual oil exportation inclined too, from 14.42 and 17.51 million tonnes in 2015 and 2016 to 39.6 and 49.93 million tonnes. Though possessing the largest proved oil reserve of 6.3 billion tonnes in Africa, Libya has suffered from political upheaval since 2011 when the country's former leader Muammar Muhammad Abu Minyar al-Gaddafi passed away. The political unrest affected the oil production in Libya and caused a huge plunge in production, from 1.6 million barrels per day in 2010 to 0.1 million barrels per day. When the instability gradually relieved and with the re-operation of oil fields and ports, the production level as well as oil exportation level increased twofold. Since the political environment of Libya is still unsteady, an oscillation in the amount of oil supply from Libya can be expected.

South Sudan reached its highest potential export level of 120.7 years of crude oil exports in 2016, then the value continues to be on the slide to 116.64 in 2017 and 100.42 years in 2018. South Sudan experienced a decrease in oil production, from 7.3 million tonnes in 2015 to 5.8 and 5.5 million tonnes in 2016 and 2017, and then the amount rose to 6.4 million tonnes in 2018. The exportation level changed in the same trend. Since 80% of South Sudan's crude oil is exported to China, a slight change in the production and exportation amount can directly impact China's import quantity from South Sudan. South Sudan became an independent country in July 2011. Due to imbalance of locations of crude oil fields, where South Sudan occupies third quarter of oil resource, South Sudan and Sudan (in north) collided over the distribution of resources. However, most of refinery equipment, pipelines and ports are located in Sudan (in the north), leaving South Sudan in a vulnerable position in refining, transporting and exporting crude oil. Under such a situation, South Sudan terminated crude oil production in some of its largest oil fields once in the past, then resumed production of those oil fields in 2018.

The potential export level of Venezuela keeps increasing from 253.06 years in 2015 to 511.36 years in 2018. At a first glace it may seem to be a good sign to have an increasing potential export level, since it indicates a longer period of oil supply. However, when the proved oil reserve stays constant, the increasing indicator suggests decline in production or exportation quantity. In the case of Venezuela, while proved reserves changed from 47 billion to 48 billion tonnes, its production quantity took a dive from 135.4 million tonnes to 77.3 million tonnes from 2015 to

2018, and export quantity shows a similar trend from 98.71 million tonnes to 63.66 million tonnes from 2015 to 2018. Since Venezuela experienced a sluggish economy in recent years (with the highest economic risk), aging equipment and stagnating production rate hindered further upgrade in the oil industry in Venezuela, therefore the production quantity declined. Moreover, the US imposed stricter sanctions towards Venezuela, resulting in a more instable political and economic environment in this country.

The dependency level shows the percentage of annual crude oil imports of China from each supplier. In all three years from 2015 to 2018, Saudi Arabia provided the most part of crude oil to China, followed by Angola, Iraq, Russia and Oman, which are the top five crude oil suppliers by the import quantities, as can be found in Table 4.2-2. Of these five countries, Oman, Russia and Saudi Arabia have average political and economic risk scores above the mean, while Angola and Iraq have scores below the mean. They all have rather stable levels of potential oil exports. The proportion of crudes imported from Saudi Arabia shows a decreasing trend from 15.07% in 2015 to 12.28% in 2018. The same trend applies to that of Oman, from 9.56% in 2015 to 7.12% in 2018. The proportion of Angola declined in the first two years, and it climbed a bit then dropped to 10.26% in 2018. The share of Iraq descended in the first three years with an increase in 2018. The portion of Russia presents an opposite trend to that of Iraq, displaying continuous increase in the first three years and then a decrease in 2018.

Table 4.2- 2 Dependency level of each supplier, from 2015 to 2018

Countries	***2015***	***2016***	***2017***	***2018***
Angola	11.53%	11.48%	12.02%	10.26%
Australia	0.71%	0.85%	0.50%	0.28%
Brazil	4.15%	5.03%	5.50%	6.85%
Colombia	2.64%	2.31%	2.22%	2.33%
Congo, Republic of	1.75%	1.82%	2.15%	2.72%
Equatorial Guinea	0.60%	0.31%	0.58%	0.54%
Gabon	0.46%	0.83%	0.91%	0.78%
Ghana	0.64%	0.67%	0.83%	0.73%
Indonesia	0.48%	0.75%	**0.35%**	**0.10%**
Iran, Islamic Republic of	7.93%	8.21%	7.43%	6.34%
Iraq	9.57%	9.50%	8.78%	9.75%
Kuwait	4.30%	4.29%	4.35%	5.03%
Libya	0.64%	0.27%	0.77%	1.86%
Malaysia	0.08%	0.63%	1.57%	1.92%
Oman	9.56%	9.20%	7.39%	7.12%
Russian Federation	8.18%	9.84%	10.62%	8.98%
Saudi Arabia	**15.07%**	**13.39%**	**12.44%**	**12.28%**
South Sudan	1.97%	1.41%	0.82%	0.73%
United Arab Emirates	3.75%	3.20%	2.42%	2.64%
United Kingdom	0.59%	1.30%	2.01%	1.67%
United States of America	**0.02%**	**0.13%**	1.81%	2.66%
Venezuela	4.77%	5.29%	5.19%	3.60%
Vietnam	0.63%	1.12%	0.56%	0.26%
Mean	3.91%	3.99%	3.97%	3.89%
Standard Deviation	4.32%	4.17%	3.61%	3.50%
Min	0.02%	0.13%	0.35%	0.10%
Max	15.07%	13.39%	12.44%	12.28%

When we categorize the suppliers based on their regions in Table 4.2-3 below, it can be clearly recognized that the quantity of imports from the Middle East made up over 50% of all imports in 2015. Though the share of imports from the Middle East slid down from 2015 to 2017, it is the largest portion of all imports in all four years. The proportion of imports from Africa and Asia fluctuated within the four years. The share of the North, Central and South America keeps growing, mainly due to the robust increase of imports from Brazil and the US which offsets the decrease of imports from Venezuela.

Table 4.2- 3 Dependency level of each region, from 2015 to 2018

Regions	*2015*	*2016*	*2017*	*2018*
Africa	17.59%	16.79%	18.07%	17.62%
Asia	10.08%	13.18%	13.61%	11.56%
Europe	0.59%	1.30%	2.01%	1.67%
Middle East	50.18%	47.79%	42.81%	43.16%
N, S&C America	11.58%	12.76%	14.72%	15.44%

By looking at individual share of each supplier country, it is hard to observe an overall trend of the dependency level of the crude oil import supply chain of China. Thus, Herfindahl-Hirschman Index (HHI) is adopted to measure the concentration degree of suppliers, as mentioned in the literature review section (Wu et al. (2009) and Yang et al. (2014)). According to the HHI formula, the share of suppliers in each region is squared and then is added up to generate the concentration level. An HHI approaching value of one indicates a higher degree of concentration of the suppliers, while an HHI getting close to zero indicates a higher degree of diversification while a lower degree of concentration. Calculation result shows that the HHI based on regions is 30.63% in 2015, 29.04% in 2016, 25.65% in 2017 and 25.48% in 2018. The decreasing trend of HHI implies that as time goes, the refineries considered a more diversified composition of suppliers and quantity imported from the suppliers in China's crude oil supply chain. However, the overall HHI in each year is relatively high, indicating there is still room for Chinese refineries to diversify their sources of imports. A more diversified source of supply means the risk of relying on a single or several suppliers is relieved, since disturbance from the single or several suppliers can be avoided by reducing the share of imports from them.

As tabulated in Table 4.1-3 in the data collection section, the longest distance between China and a given supplier country resides in the pair of the US and China, which is approximately 17,507 nautical meters from the Gulf Coast to Qingdao port. Assuming an oil tanker, regardless of its size, travels in a constant and economical speed of 13.5 knots per hour, 24 hours per day, the approximate travel time can be estimated, as shown in Table 4.2-4. On the longest route, it takes a tanker 54 days to transit from the US to Qingdao, which is almost twice the average of 24.9 days. Other countries in South and Central America, west and south Africa as well as in Europe manifest longer travel times than the mean, while Asian countries show much less travel time than others due to closer location. Longer distance usually indicates larger uncertainty and more potential risks (Zhang, et al., 2013), however, other risk factors should be taken into account as well.

Table 4.2- 4 Estimation of travel time from supplier countries

Region Based on Routes	Routes and Chokepoints	Supplier Countries	Distance between Supplier and Qingdao Port, China (nm)	Estimation of travel time (days)
Middle East	Hormuz Strait - Straits of Malacca - South China Sea	Iran, Islamic Republic of	6,198	19.1
		Iraq	6,358	19.6
		Kuwait	6,288	19.4
		Oman	5,609	17.3
		Saudi Arabia	6,164	19.0
		United Arab Emirates	6,004	18.5
South & Central America	North part of South America - Cape of Horn - Pacific Ocean - Straits of Malacca - South China Sea	Brazil	12,297	38.0
		Colombia	16,301	50.3
		United States of America	17,507	54.0
		Venezuela	15,545	48.0
Europe & North Africa	Suez Canal - Bab el-Mandeb Strait - Straits of Malacca - South China Sea	Libya	7,915	24.4
		South Sudan	6,741	20.8
		United Kingdom	11,017	34.0
West & South Africa	Cape of Good Hope - Straits of Malacca - South China Sea	Angola	9,683	29.9
		Congo, Republic of	9,727	30.0
		Equatorial Guinea	10,277	31.7
		Gabon	10,080	31.1
		Ghana	10,508	32.4
South East Asia & Pacific	Straits of Malacca - South China Sea	Australia	3,582	11.1
		Indonesia	2,660	8.2
		Malaysia	2,467	7.6
		Vietnam	1,963	6.1
Japanese Sea	Japanese Sea - East China Sea	Russian Federation	1,001	3.1

Table 4.2-5 lists the dependency level of each chokepoint. Straits of Malacca, the second busiest transit chokepoint in the world[9], is the most important chokepoint for the crude oil import supply chain of China. It is the only waterway connecting the Pacific Ocean and the Indian Ocean. The Straits of Malacca is co-governed by Malaysia, Singapore and Indonesia (see Figure 4.2-1 below). The quantity of crude oil carried by tankers traveling through the Straits of Malacca comprises over 80% of all imports in China each year, from 2015 to 2018. This is because crude oil tankers from the Middle East, Africa and Europe have to transit through the Straits of Malacca to approach China, while the tankers from the east side of the Pacific Ocean need to stop by the Straits of Malacca to be filled up for the rest of their journey. Depending highly and solely on the Straits of Malacca leaves Chinese refineries lack of choice of transportation routes, coercing the refineries to be exposed to greater uncertainties when this chokepoint is blocked down. Another chokepoint that rises or attention is the Hormuz Strait. Located at the throat of waterway in the Middle East (see Figure 4.2-2), the Hormuz Strait is encompassed by countries that are main oil suppliers worldwide, such as Iran, Saudi Arabia, United Arab Emirates, Oman, etc. The dependency of the Hormuz Strait declined throughout the four years, however, the share of imports passing through this chokepoint still maintained a rather high level of 53% to 45%. It can be concerning especially when tension between Iran and the West continues to rise nowadays, and Iran threats to shut down the Hormuz Strait. The oil imports from the Middle East cover over half of annual crude imports to China, and all of the Middle East crudes have to be transported via the Strait of Hormuz. The negative impact on the Hormuz Strait can be devastating to the refineries in China.

[9] The US Energy Information Administration (EIA), World oil transit chokepoints, https://www.eia.gov/beta/international/regions-topics.php?RegionTopicID=WOTC (last date of access: August 26th, 2019)

Table 4.2- 5 Dependency level of each chokepoint

Chokepoint Regions	*Chokepoints*	*2015 (%)*	*2016 (%)*	*2017 (%)*	*2018 (%)*
Middle East	Hormuz Strait	53.20%	52.43%	46.59%	45.53%
South America	Cape of Horn	8.70%	8.74%	10.88%	13.23%
Mediterranean & North Africa	Suez Canal-Bab el-Mandeb Strait	3.48%	3.28%	4.49%	4.52%
West & South Africa	Cape of Good Hope	15.81%	16.12%	17.36%	15.99%
South East Asia	Straits of Malacca	84.55%	84.96%	83.55%	82.06%
Japanese Sea	Japanese Sea	5.34%	6.13%	5.32%	6.10%

Figure 4.2- 1 Map of the Strait of Malacca

Figure 4.2- 2 Map of the Strait of Hormuz

This figures are adapted from The US Energy Information Administration (EIA), World oil transit chokepoints, https://www.eia.gov/beta/international/regions-topics.php?RegionTopicID=WOTC (last date of access: August 26th, 2019)

From Table B-2 in the Appendix B, a downward trend of the number of piracy attacks can be observed, that is from 87 incidents in 2015 to 81 incidents in 2016, 77 incidents in 2017 and 75 incidents in 2018. By looking at the number of piracy incidents in each region, which is summarized in Table 4.2-6, we have discovered that pirate attacks happened most in South East Asia, accounting for 109 incidents in total during the four years. Following is West Africa, where there were 96 attacks towards tankers from 2015 to 2018. Ideally, tankers should avoid including the mentioned areas in their routes, however, for the tankers to China, South East Asia and West Africa are regions that are hard to detour. As discussed above, the Straits of Malacca, which is the key chokepoint in South East Asia and the only waterway from main oil suppliers to China, bears over 80% of annual total crude oil imports in China. The West Africa countries provide for almost 20% of all crude oil imports per year to China. One significant difference between the two regions is that, the number of piracy attacks in South East Asia dropped sharply, from 53 in 2015 to 12 in 2018; while the number of incidents in West Africa oscillated in a volatile manner. The volatility can be attributed to the number of attacks happening in Nigeria, from 7 attacks in 2015 surging to 27 attacks in 2016, then with a slight drop to 16 incidents in 2017 and re-bouncing to 25 incidents in 2018. The decline in South East Asia area ascribes to increased patrol in this area and more cooperation of law enforcement departments of neighboring nations. Nigeria is regarded as a country that has rich oil reserves and is lucrative in exporting crude oil, and it is the transportation hub for adjacent countries. Illegal armed forces targeted this area especially on anchored or idling tankers due to low speed of the vessels and high value of the cargoes, as well as lax security actions along the coastline. The west side of South America, leading to Venezuela and Columbia, has become the new hotspot for piracy incidents occurrences. Political upheaval, economic instability and falling rate of employment in Venezuela are reasons behind the increasing number of piracy attacks in that area.

Table 4.2- 6 Number of piracy attacks in each region (from 2015 to 2018)

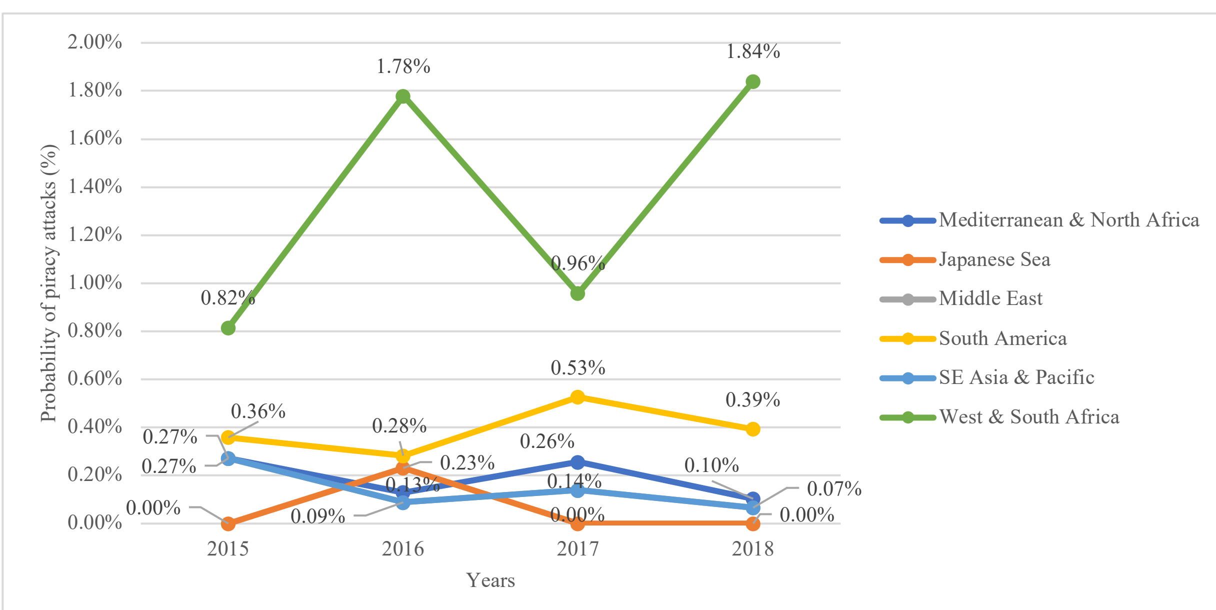
Regions of Piracy Incidents	***2015***	***2016***	***2017***	***2018***
Indian Sub-Continent	13	9	2	6
Middle East	0	0	1	0
Red Sea	0	2	6	2
South America (West)	0	4	0	0
South America (East)	3	7	15	13
South and East Africa	2	4	1	2
South China Sea	7	6	6	4
South East Asia	53	16	28	12
West Africa	9	33	18	36
Grand Total	**87**	**81**	**77**	**75**

Although the number of piracy incidents on tankers is conspicuous, chances of being attacked are rather low, given the large volume of traffic flow in each region. By using the model introduced in the modelling section, probabilities of piracy attacks are calculated. From Table 4.2-7 and Chart 4.2-3, supplier countries in West Africa and routing via the Cape of Good Hope is threatened by pirates at the highest rate in each year. Especially in 2016 and in 2018, probability of piracy attacks exceeded 1% and reached 1.78% and 1.84% respectively. The reason behind such high rate is that tankers from that area have to sail through both West Africa and South East Asia, the two piracy hotspots, making the West and South Africa route (via Cape of Good Hope - Straits of Malacca - South China Sea) the riskiest one for the Chinese refineries.

Table 4.2- 7 Probability of piracy attacks in each region (from 2015 to 2018)

Regions of Supplier Countries	***2015 (%)***	***2016 (%)***	***2017 (%)***	***2018 (%)***
Mediterranean & North Africa	0.2717%	0.1295%	0.2564%	0.1030%
Japanese Sea	0.0000%	0.2309%	0.0000%	0.0000%
Middle East	0.2717%	0.0885%	0.1392%	0.0662%
South America	0.3582%	0.2824%	0.5260%	0.3929%
SE Asia & Pacific	0.2717%	0.0885%	0.1392%	0.0662%
West & South Africa	0.8152%	1.7789%	0.9580%	1.8395%

Chart 4.2- 3 Probability of piracy attacks in each region (from 2015 to 2018)



The rent rates of spot-chartered tankers are measured based on tonnage of each cargo that an oil tanker carries for an order, while distance between loading and discharging points are incorporated in the rates. We assume that there is only one loading port and one discharging port for each tanker fulfilling each order. Chart 4.2-4 shows the weekly rents of spot-chartered oil tankers from 2015 to 2018, and Chart 4.2-5 presents average rates of spot-chartered oil tankers from six regions as in Table 4.2-4. In Chart 4.2-4, rent rates of oil tankers loading from the Middle East, South and Central America, North Africa and West Africa share a similar trend, while rates of tankers from Russia, South East Asia and Pacific share more similar trends. It can be explained by the geographical distance between the loading areas and China, as well as the sizes of tankers rented. For the supplier countries in the first group of loading areas (Middle East, South and Central America, North Africa and West Africa), longer distance (above 5,500 nm, as in Table 4.2-4) requires larger tankers, such as VLCC and ULCC, in order to be cost efficient and profitable. For those in the second group (Russia, South East Asia and Pacific), the distances between supplier countries and China are below 3,500 nm, hence smaller tankers can perform better in feeding smaller refineries. Within the first group, tankers sailing form South and Central America need to travel the longest distance to reach their destination, thus the unit rate is the highest most of time. Distance from West Africa to China is slightly shorter than that from South and Central America, the unit rates are slightly lower too in most cases. The distance from North Africa (except the UK) to China is similar to the distance from the Middle East to China, however, the rates of the former are much higher than that of the latter due to the sizes of tankers used. Most of the crude oil suppliers in the North Africa locate along the Mediterranean Sea and need to transit through the Suez Canal. As explained in earlier sections, tankers traversing through the Suez Canal are constrained by certain limits. The maximal tanker that is allowed to pass through the Suez Canal is the Suezmax, which has a typical deadweight of about 160,000 tonnes, only half of the deadweight size of a VLCC. Tankers from the Middle East are not restricted, therefore VLCC and ULCC are often chosen and the unit rate of leasing a spot-chartered tanker is lower. The average unit rents of the tankers from six regions show a clearer trend in Chart 4.2-5. All of them demonstrate a decreasing trend from 2015 to 2017, an then a modest rise from 2017 to 2018.

Chart 4.2- 4 Weekly rents of spot-chartered oil tankers (Unit: USD per tonne, from 2015 to 2018)

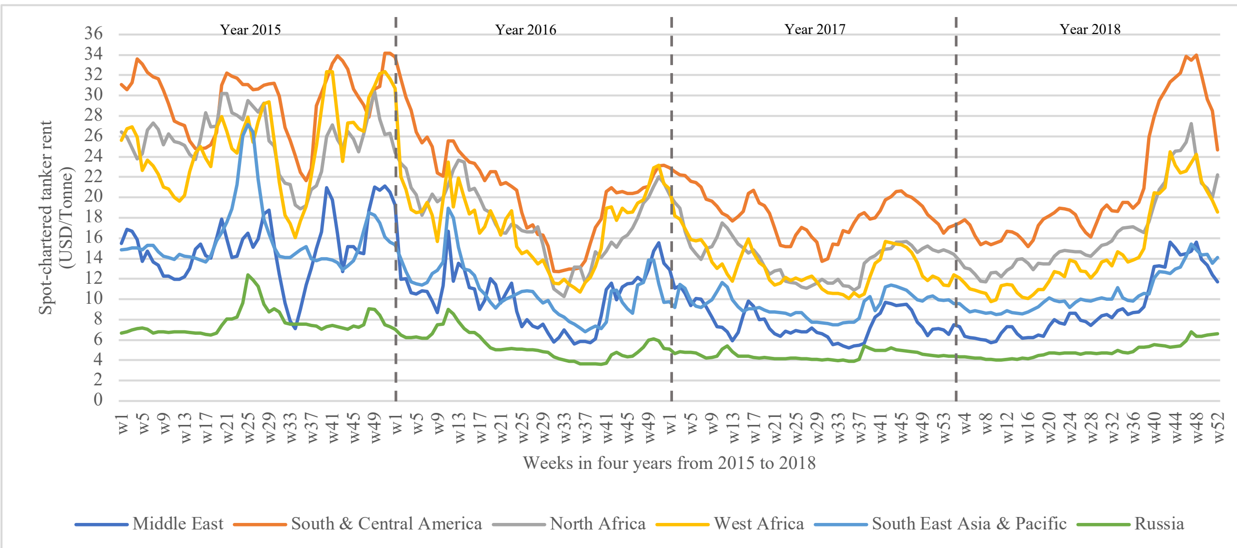
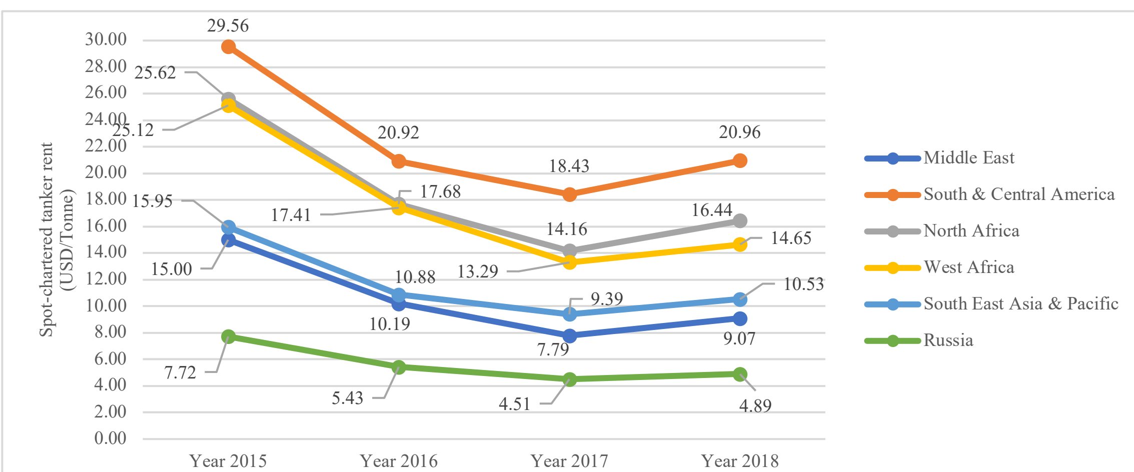


Chart 4.2- 5 Average rents of spot-chartered oil tankers (Unit: USD per tonne, from 2015 to 2018)

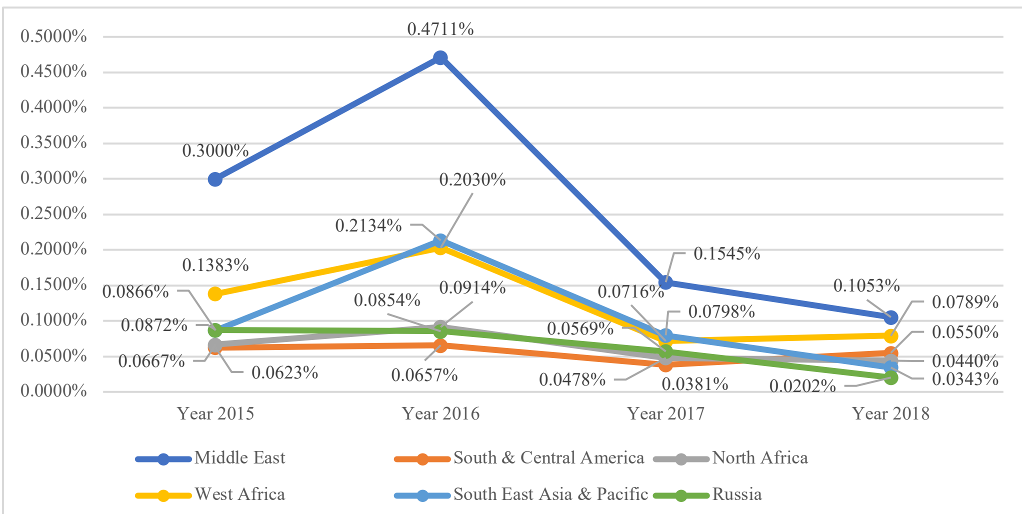


When we look into volatility of the freight rate, fluctuation of rent rates in the Middle East is the largest in all four years, meaning that for tankers from this area, the relative changes of rents between the prior week and the later week are the most significant among all regions (see Table 4.2-8 and Chart 4.2-6).

Table 4.2- 8 Volatility of rent rates of spot-chartered crude oil tankers (from 2015 to 2018)

Regions	*Year 2015*	*Year 2016*	*Year 2017*	*Year 2018*
Middle East	0.3000%	0.4711%	0.1545%	0.1053%
South & Central America	0.0623%	0.0657%	0.0381%	0.0550%
North Africa	0.0667%	0.0914%	0.0478%	0.0440%
West Africa	0.1383%	0.2030%	0.0716%	0.0789%
South East Asia & Pacific	0.0866%	0.2134%	0.0798%	0.0343%
Russia	0.0872%	0.0854%	0.0569%	0.0202%

Chart 4.2- 6 Volatility of rent rates of spot-chartered crude oil tankers (from 2015 to 2018)



Since both rise and decrease in rents are considered, the volatility measures the absolute changes. Although for each region the volatility is rather small, the regions with larger fluctuation levels still represent more uncertainties in freight rate prediction for the refineries, especially when their purchase is done several months prior to the date of loading and delivery. Besides, since VLCCs are often used as carriers of Middle East cargoes, where those tankers have deadweight tonnage

(DWT) between 160,000 DWT to 320,000 DWT, fluctuation of 1 US dollar of the unit rent rate en this route may result in a cost saving or a loss of up to 320,000 US dollars. The higher the volatility, the more uncertainty with such gain or loss, which is riskier for a refinery.

4.3 Analysis Based on Composite Indicator (CI) Scores

4.3.1 Indicator Shares without Restrictions

Just to recall the concept of indicator share, which was mentioned in the modelling section from the constraint (18), it is the ratio of a given weighted indicator of a country to the total composite indicator (CI) score of that country. Based on the concept, the total CI score of a country can be understood as the sum of the weighted indicators with non-zero weights. Those non-zero weighted indicators contribute to the total CI score, and the larger share they take, the more importance they bear in the total CI score. When no restriction is enforced on the share, the DEA-like model can choose weights for the indicators with full freedom and flexibility. At this point in our case study, we will let the DEA-like model work freely without constraints on the share of non-zero weighted indicators to the total CI score. The DEA-like model without constraint (18) will be applied to the indicator sets of the 23 supplier countries. The model was run on Excel 2016 in the Solver Add-in. The CI scores for each country can be found in Table 4.3-1.

Table 4.3- 1 Composite indicator (CI) scores from 2015 to 2018, without restrictions on indicator shares

Supplier Countries	2015	2016	2017	2018
Angola	0.610	0.607	0.621	0.593
Australia	1	1	1	1
Brazil	1	1	1	0.806
Colombia	1	1	1	0.773
Congo, Republic of	0.566	0.569	0.595	0.550
Equatorial Guinea	0.498	0.519	0.826	0.491
Gabon	0.742	0.736	0.758	0.723
Ghana	0.763	0.765	0.777	0.746
Indonesia	1	1	1	1
Iran, Islamic Republic of	0.703	1	0.730	0.928
Iraq	0.646	1	0.690	0.985
Kuwait	0.898	1	0.903	0.991
Libya	1	1	1	0.843
Malaysia	1	1	1	1
Oman	0.759	1	0.779	0.899
Russian Federation	1	1	1	1
Saudi Arabia	0.836	1	0.841	0.954
South Sudan	1	1	1	0.795
United Arab Emirates	0.923	1	0.916	0.982
United Kingdom	1	1	1	1
United States of America	1	1	1	0.969
Venezuela	1	1	1	1
Vietnam	1	1	1	1

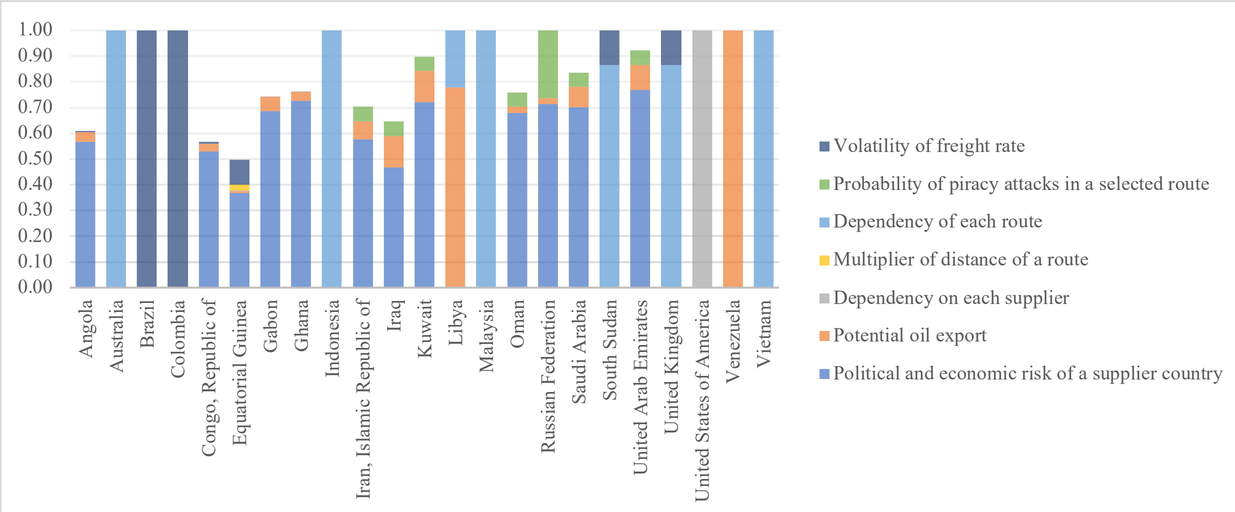
In this case, the normalized indicators and CI scores indicate the larger the numbers, the better the performance of supplier countries, as explained in the modelling section. From observation of data in Table 4.3-1, 12 countries reach their CI scores of 1 under most favorable weights in 2015. Those countries are benchmarks to the other countries which show leeway from a score of 1. In 2016, the number of outperforming countries grows to 18, and in the following two years 2017 and 2018, the numbers of countries with CI scores of 1 are 12 and 7, respectively. Among the best performing countries in each year, Australia, Indonesia, Malaysia, Russian Federation, United Kingdom, Venezuela and Vietnam get CI scores of 1 in all four years, from 2015 to 2018. For each supplier country, the weights chosen under complete freedom are the most favorable weights and they assure the countries' CI scores approaching the best level they can be at. However, issues may occur due to the absolute freedom. As presented in Table 4.3-2, there are many zero-value weights allocated to indicators for each country, indicating that those indicators are omitted and make no contribution to the total CI score. The reason behind this phenomenon is described by Cherchye, et al. (2007, p125) as a choice of the "brilliant performers". It happens when some indicators dominate the others. The mechanism of the model enforces the dominating indicators to be assigned with larger weights and the dominated ones to be assigned with zero, in order to maximize the total CI score. It is because the model reckons that one or more of their indicators are less competitive than the dominating ones, thus, the less competitive ones are regarded as not important in compiling the total CI score and weights of zero are assigned to them.

Table 4.3- 2 Most favorable weights of indicators chosen by DEA-like model (without restriction, in 2015)

Supplier Countries	*Political and Economic Risk*	*Potential Oil Export*	*Dependency on Each Supplier*	*Multiplier of Distance of a Route*	*Dependency of Each Route*	*Probability of Piracy Attacks*	*Volatility of Freight Rate*
Angola	0.9735	0.4920	0	0	0	0	0.0131
Australia	0	0	0	0	1	0	0
Brazil	0	0	0	0	0	0	1
Colombia	0	0	0	0	0	0	1
Congo, Republic of	0.9735	0.4920	0	0	0	0	0.0131
Equatorial Guinea	0.7637	0.3792	0.0281	0.2380	0	0	0.2172
Gabon	0.9813	0.5011	0.0478	0	0	0	0
Ghana	0.9813	0.5011	0.0478	0	0	0	0
Indonesia	0	0	0	0	1	0	0
Iran	0.9266	0.4865	0	0	0	0.2626	0
Iraq	0.9266	0.4865	0	0	0	0.2626	0
Kuwait	0.9266	0.4865	0	0	0	0.2626	0
Libya	0	0.9113	0	0	0.2295	0	0
Malaysia	0	0	0	0	1	0	0
Oman	0.9266	0.4865	0	0	0	0.2626	0
Russian Federation	0	0	0	1	0	0	0
Saudi Arabia	0.9266	0.4865	0	0	0	0.2626	0
South Sudan	0	0	0	0	0.8957	0	0.1451
United Arab Emirates	0.9266	0.4865	0	0	0	0.2626	0
United Kingdom	0	0	0	0	0.8957	0	0.1451
United States of America	0	0	1	0	0	0	0
Venezuela	0	1	0	0	0	0	0
Vietnam	0	0	0	0.5453	0.7219	0	0

Another observation of Table 4.3-2 reveals that, for eight countries, only the most advantageous indicators are assigned weights, and the weights are 1, meaning that the sole indicator represents the CI score for that country. It can also be noticed from the contribution of indicator shares in Chart 4.3-1 that eight out of twelve countries with the CI scores of 1 have only one indicator that contributes to the total CI score, while other four countries with maximal CI scores have only two or three non-zero weighted indicators that comprise the total CI score. It can be concerning, since when we investigated the underlying meanings of the indicators, drawback appears. In the situation mentioned above, where the CI score is determined by only one or a few weighted indicators, sometimes it may deviate from reality. For instance, the CI score for Brazil is 1, which is derived solely by the indicator of volatility of freight rate. Though attaining a high score, it does not necessarily make Brazil a perfect supplier for the refineries in China. When looking at other indicators that are ignored by assigning zero-value weight, we discovered that Brazil ranks number 22 in potential oil export, meaning that Brazil is less likely to provide stable supply of crude oil in the future, compared with other suppliers. It ranks number 20 in multiplier of distance, indicating that the travel distance for oil tankers from Brazil to China is longer than from most of other suppliers. Longer voyage time enforces the decision makers to plan ahead a longer time, leaving more uncertainties at the planning stage. Brazil ranks number 15 in both dependency of suppliers and probability of piracy attacks, which are at moderate level. What are mentioned above are important dimensions in evaluating the supplier countries and therefore the supply chain of the refineries. However, they are ignored by the DEA-like model for the purpose of maximizing the CI score. It may cause the decision makers to doubt the reliability of the model and the results.

Chart 4.3- 1 Contribution of each indicator in all supplier countries' total CI score (without restriction, in 2015)



To sum up, having no restrictions on indicator share guarantees the full freedom for the model to select the most favorable weights for each country. Therefore, the model generates the highest CI score, by allocating zero-value weights to the disadvantageous indicators and choosing outstanding indicators meticulously. Under such circumstance, the impact and importance of those less advantageous indicators in real life is ignored by the weight-assigning technique, and the partial consideration of the indicators may lead to biased conclusion, even if the weight-assigning technique is objective. Same findings are discovered in all the other three years, from 2016 to 2018. Furthermore, we can expect that if any restrictions are imposed on indicator shares, the best performing countries with restrictions are always included in the collection of the best performing countries without restrictions. It is because that the countries with freely selected weights will always produce the best CI scores and any restrictions imposed can only reduce the CI scores.

In this respect, restrictions on the indicator shares will be imposed, enforcing countries to consider indicators as many as possible, rather than only a few indicators, in providing a fairer analysis in regard to reality situations.

4.3.2 Indicator Shares with Restrictions

The restrictions are used to enforce each weighted indicator to fall within a range of proportion of the whole CI score, so that the contribution of each weighted indicator can be more compliant to the reality. It is an indirect way of restricting the weights assigned to each indicator, since the constraints are imposed on the share of weighted indicators (calculated by each weighted indicator over the sum of weighted indicators), as in the constraint (18) in the modelling section. The concept of restrictions on the indicator shares is based on the Budget Allocation method, which is commonly used in financial planning to prevent deficit by allocating portions of budgets to each expenditure unit. One can imagine the total CI score as the "budget" and each weighted indicator as a portion of the budget. Thus, the restriction on indicator shares is a limitation on relative sizes of both the weighted indicator and the total CI score. Moreover, due to the form of "share", this restriction is unit invariant. However, according to the constraint (18), the lower and upper bounds are difficult to be determined with full objectivity. Cherchye, et al. (2007) in their paper recommended to incorporate experts' opinion in deciding on the restriction bounds. However, we have no source of any expert in this case. In this regard, we took trial and error to find out the impact of the constraints to the CI scores.

In this part, five sets of restrictions are exercised on the indicator shares. The restrictions are imposed in a gradually tightening order. Firstly, a lower bound of 0.0001 and no upper bound is set to the indicator shares. Since 0.0001 can be regarded as a small enough number, applying 0.0001 as the lower bound is only to avoid the indicator share to be zero. Then, for the purpose of observing the impact of tightening the lower bound, it is set to 0.005, with no upper bound imposed. An upper bound of 0.6 is added to the model later to test the impact of upper bound, and the lower bound remains at 0.005. Afterwards, the lower bound shifts to 0.05, while the upper bound is still 0.6. Lastly, the upper bound is further tightened to be 0.3. Based on the five sets of weights, various CI scores and different indicator shares are generated. Data in 2015 is used to provide an example. The comparison of CI scores and contribution of indicator shares of each country are illustrated in the charts (Chart 4.3-2 (1) to (6)) below. In these charts, "0." represents no restriction on indicator shares; "i." means the indicator shares fall into range of [0.0001, +∞); "ii." indicates the range for indicator shares is [0.005, +∞); "iii." is where the range is [0.005, 0.6]; "iv." is where the range is [0.05, 0.6]; and "v." is where the range is [0.05, 0.3]. Specific numbers of each indicator share and total CI score for each supplier country can be found in the Appendix B in Table B-3.

Chart 4.3-2 (1) Comparison of CI scores and indicator shares under various sets of weights (2015)

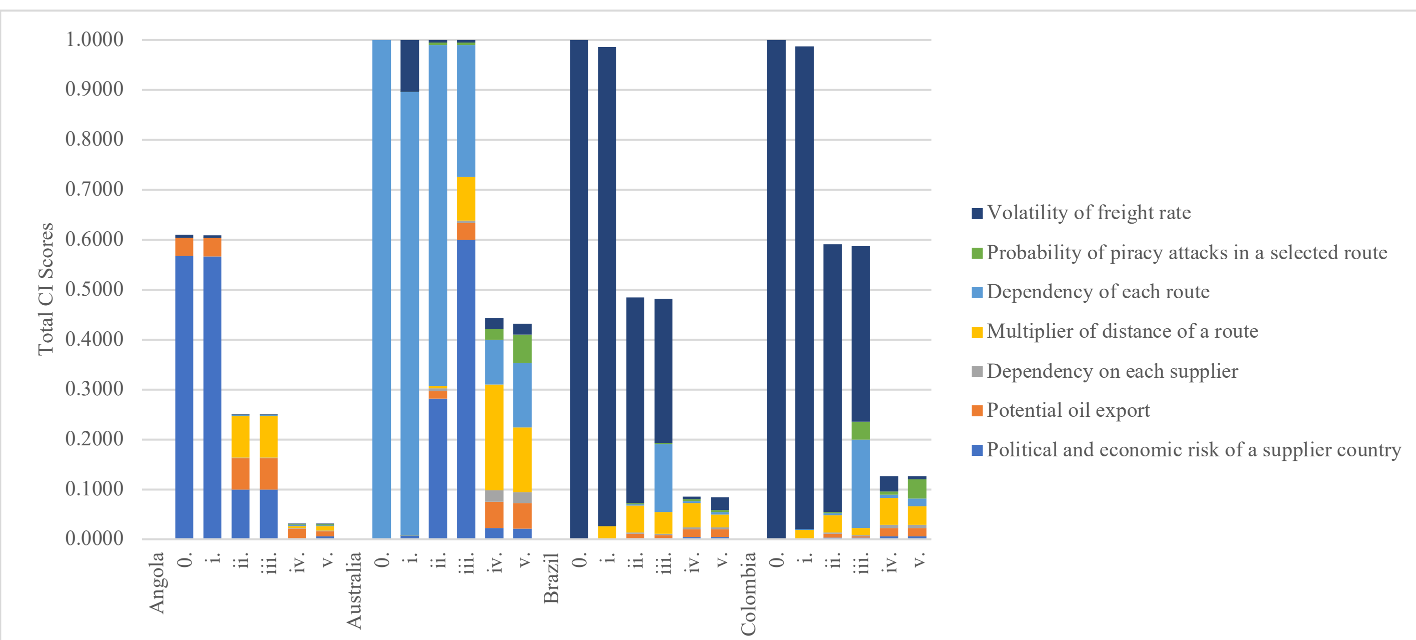


Chart 4.3-2 (2) Comparison of CI scores and indicator shares under various sets of weights (2015)

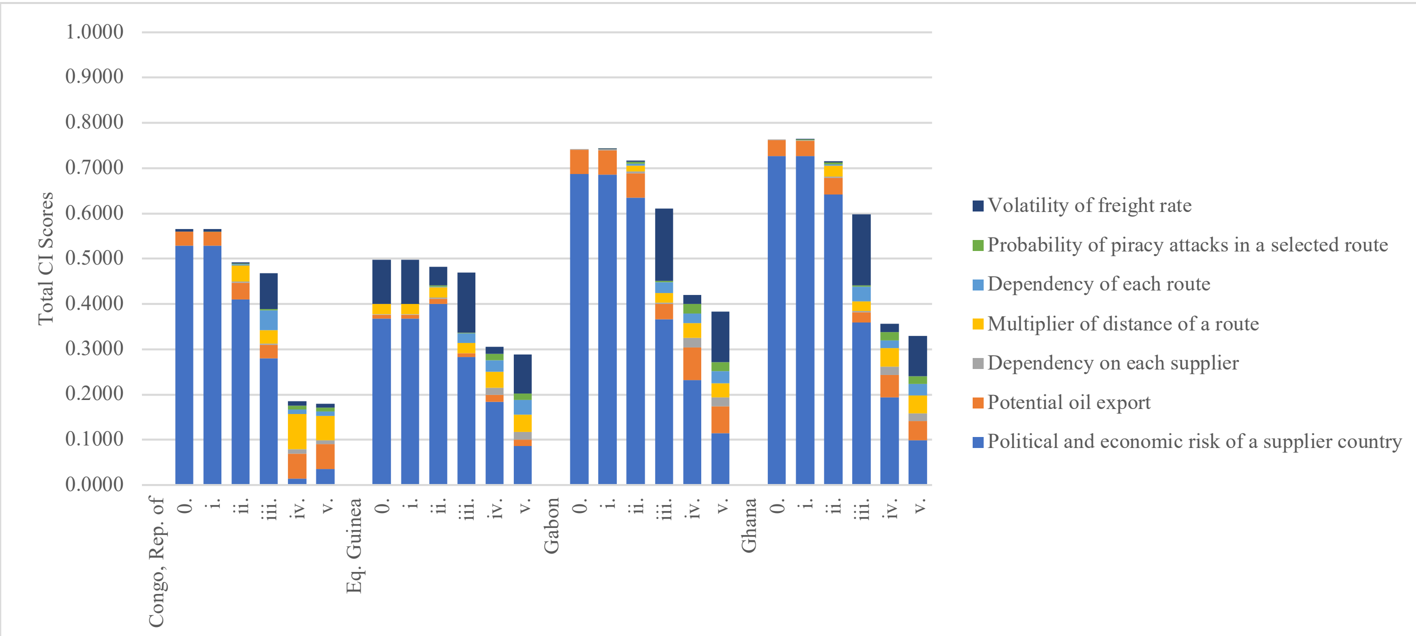


Chart 4.3-2 (3) Comparison of CI scores and indicator shares under various sets of weights (2015)

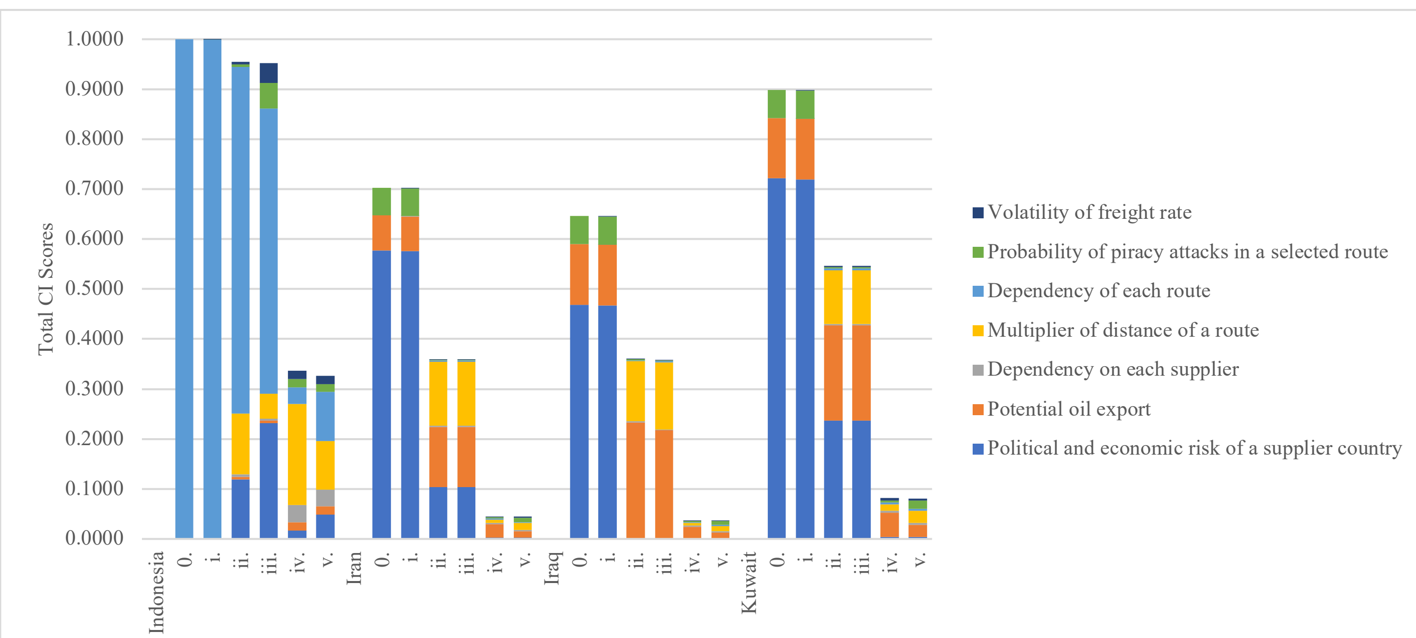


Chart 4.3-2 (4) Comparison of CI scores and indicator shares under various sets of weights (2015)

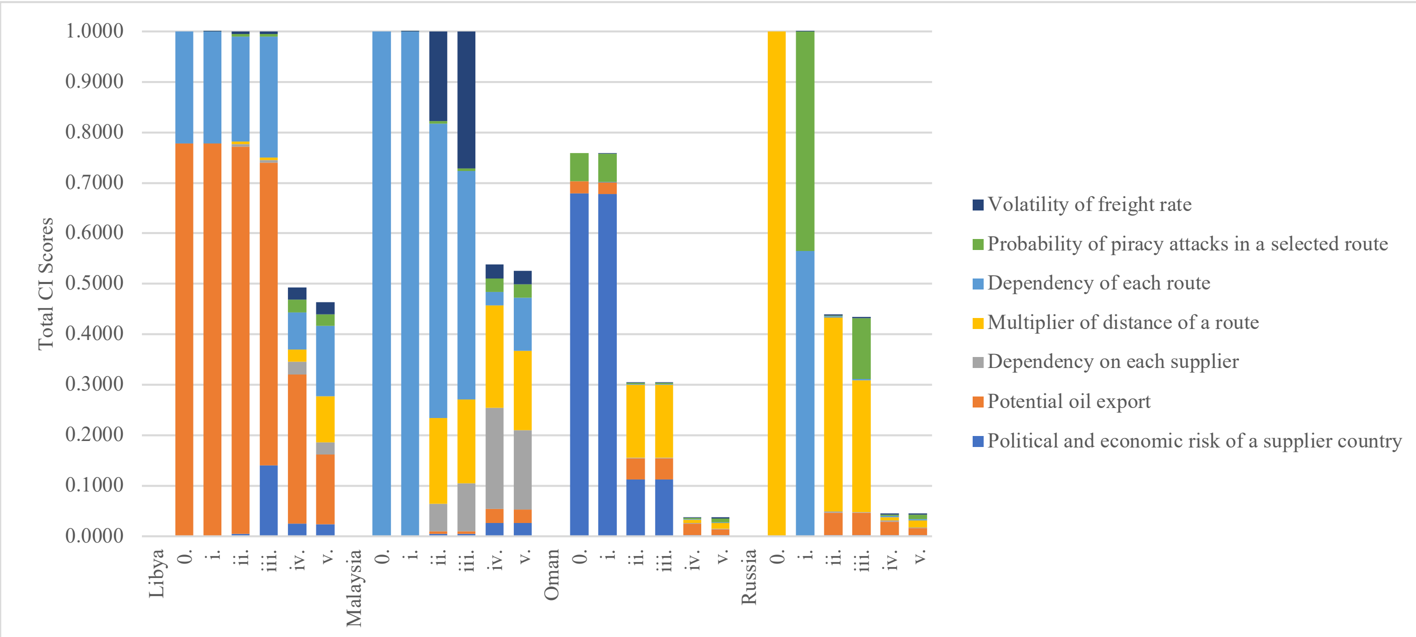


Chart 4.3-2 (5) Comparison of CI scores and indicator shares under various sets of weights (2015)

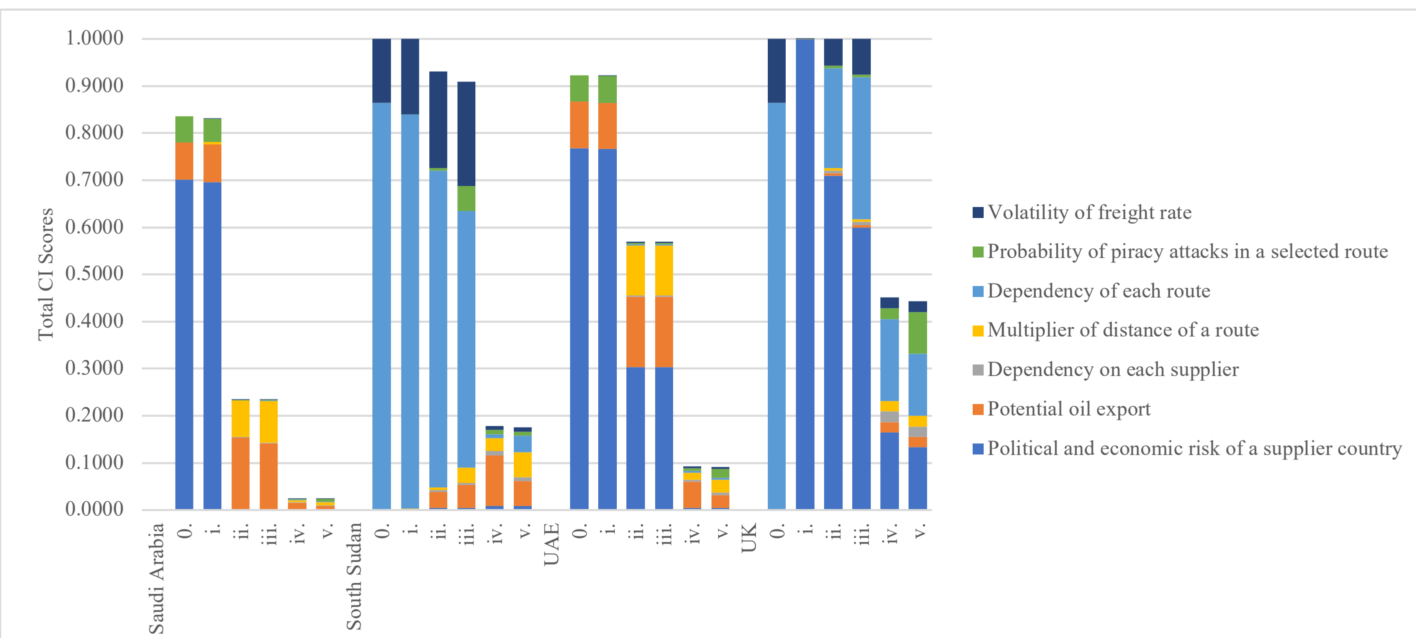
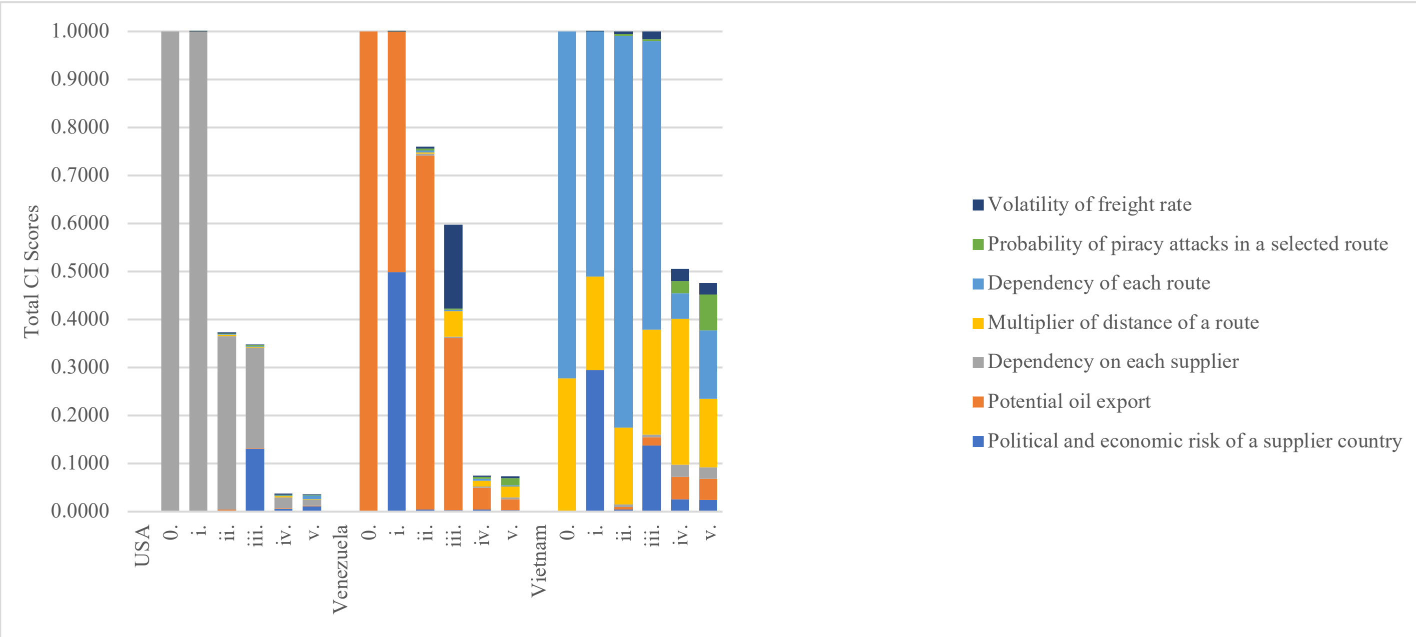


Chart 4.3-2 (6) Comparison of CI scores and indicator shares under various sets of weights (2015)



From the Charts 4.3-2 (1) to (6), when the lower bound changes from zero to 0.0001, which is a number very close to zero, the overall CI scores and composition of indicator shares do not change much, compared with when the lower bound increases from 0.0001 to 0.005 in situation ii, while the upper bound is unlimited. In the latter situation, when the lower bound of 0.005 is applied to the indicator shares, more than half of the supplier countries show a significant plunge (≥ 20%) in the total CI score. When an upper bound of 0.6 is added on top of the lower bound of 0.005, only Venezuela experiences a significant decrease (≥ 20%) in its CI score. Gabon and Ghana have decline of 14.86% and 16.40% respectively, while for the remaining countries, ten show a decline of less than ten percent and the other ten do not show any change in their total CI scores. When the lower bound raises from 0.005 to 0.05 and the upper bound maintains at 0.6 as in situation iv, all of the supplier countries experience shrinking in their CI scores for more than 30%, and eighteen of them show more than 50% of shrinkage in their CI scores. In situation v, when the lower bound is constant and the upper bound moves to 0.3 from 0.6, the decrease rates of all the supplier countries fall below ten percent. Based on the observation, a hypothesis arises that the lower bounds appear to be more binding than the upper bounds in this case.

In order to figure out the reason behind it, we investigated the sensitivity report of each country and looked at shadow prices of the indicators under the upper and lower constraints in each situation. The shadow price in the context of DEA measures the impact of relaxing or straining one unit of constraint on the change in the object value of the optimal solution, which is the CI score in our case. If a constraint is an upper bound constraint, then a positive shadow price indicates the constraint is binding; if a constraint is a lower bound constraint, then a negative shadow price implies a binding constraint. While for a non-binding constraint, the shadow price is always zero.

By observing how many times the binding constraints appear in either upper or lower bounds, we found that in each situation, the number of binding constraints on the lower bound side of each country occurs more frequently than that on the upper bound side. The number of binding upper or lower constraints under each situation can be found in Table B-4 in the Appendix B.

In Table B-4, the shadow prices on the upper bound side of situation i and ii are zero, since there is no restriction imposed on the upper bounds, and thus the upper bounds are not binding. On the lower bound side of these two situations (i and ii), there are 75 and 93 negative shadow prices respectively, meaning that when the lower bounds are applied to the indicator shares, in 75 and 93 times, the lower bounds are binding. In the remaining three situations (iii, iv and v) when the upper bounds are applied or tightened, there are 14, 15 and 42 times that the shadow prices are positive, indicating that when each of the upper bound is applied to indicator shares, there are 14, 15 and 42 instances when the upper bound is binding; for the lower bounds in situation iii, iv and v, there are 70, 106 and 77 times that the shadow prices are negative, showing in each respective case the lower bound is binding. In each case, the numbers of binding constraints on the lower bound side appear more often than that on the upper bound side. Moreover, the absolute value of shadow prices on the lower bound side are observed to be much larger than the absolute value of shadow prices on the upper bound side. This observation implies that when changing one unit of the right-hand side constraint within the allowable increase and decrease ranges, the one-unit change made on lower bounds are more influential to the overall CI scores than that change made on upper bounds. To be specific, since the shadow price value for a lower bound constraint is negative, increasing one unit of a binding lower bound means to decrease the total CI score by the shadow price value. Also, because the shadow price value for an upper bound constraint is positive, declining one unit of a binding upper bound means to decrease the total CI score by the shadow price value. Thereby, the impact on the total CI score of tightening one unit of a binding lower bound can be larger than that of a binding upper bound. Given the number of binding lower bound constraints are much larger than the number of binding upper constraints in each situation, it is possible to assume that the lower bounds are more binding than the upper bounds in our case. In this sense, when selecting bounds, especially the lower bounds in this case, more caution should be taken, since setting various bounds can cause significant changes in the total CI scores. In the following analysis, the bounds of [0.05, 0.6] are chosen due to the following reasons. In the previous bound ranges (i, ii and iii), there are multiple countries reaching the benchmarking CI scores of one. However, it is hard to distinguish which benchmark country performs better than the others. Under the constraining bounds of [0.05, 0.6], the CI scores are distinguished and ranked without overlap, entailing a clearer comparison among countries. As for the upper bound side, the upper bound of 0.3 enforces each indicator share to stay below 30% of the total CI score of a given country, making the advantageous indicators less important in composing the total CI score. Therefore, a more relaxed upper bound of 0.6 will be used.

Given the restrictions of [0.05, 0.6] on the indicator shares, CI scores of each country in four years, from 2015 to 2018, are generated, as listed in Table 4.3-3.

Table 4.3- 3 CI scores for supplier countries (from 2015 to 2018)

CI Score	in 2015	in 2016	in 2017	in 2018
Angola	0.032	0.176	0.317	0.126
Australia	0.444	0.647	0.904	0.697
Brazil	0.085	0.188	0.247	0.197
Colombia	0.126	0.224	0.184	0.161
Congo, Republic of	0.185	0.353	0.415	0.225
Equatorial Guinea	0.306	0.264	0.391	0.267
Gabon	0.420	0.417	0.490	0.313
Ghana	0.356	0.396	0.333	0.278
Indonesia	0.337	0.261	0.191	0.100
Iran, Islamic Republic of	0.045	0.240	0.412	0.210
Iraq	0.038	0.215	0.411	0.160
Kuwait	0.081	0.378	0.514	0.252
Libya	0.493	1.000	0.916	0.546
Malaysia	0.538	0.403	0.447	0.255
Oman	0.038	0.219	0.390	0.186
Russian Federation	0.045	0.241	0.513	0.199
Saudi Arabia	0.024	0.163	0.327	0.134
South Sudan	0.179	0.797	0.925	0.661
United Arab Emirates	0.093	0.409	0.563	0.335
United Kingdom	0.451	0.281	0.335	0.194
United States of America	0.037	0.044	0.072	0.072
Venezuela	0.076	0.407	0.643	0.338
Vietnam	0.505	0.657	0.896	0.562

The scores show rankings of countries in each year. Based on the scores shown in the table above, Table 4.3-4 tabulates countries with top three highest CI scores in each year. Countries such as Vietnam, Libya, South Sudan and Australia appear more than once in the top-three echelon. Vietnam, Libya and South Sudan occur three times and Australia shows twice. The higher the score indicates the less level of risks of the import activities in respect of all indicators of a country.

On the opposite, the lower the score means the higher level of risks that the refineries have to bear during the crudes import process. Supplier countries with the least three CI scores can also be found in Table 4.3-4. From the table we can see that the US occurs four times in the echelon, while Angola takes place three times, and Saudi Arabia and Indonesia show twice.

Table 4.3- 4 Supplier countries with top three and least three CI scores (from 2015 to 2018)

	Year 2015		***Year 2016***		***Year 2017***		***Year 2018***	
	Country	**CI Score**	**Country**	**CI Score**	**Country**	**CI Score**	**Country**	**CI Score**
Top 1st	Malaysia	0.538	Libya	1	South Sudan	0.925	Australia	0.697
Top 2nd	Vietnam	0.505	South Sudan	0.797	Libya	0.916	South Sudan	0.661
Top 3rd	Libya	0.493	Vietnam	0.657	Australia	0.904	Vietnam	0.562
Least 1st	Saudi Arabia	0.024	US	0.044	US	0.072	US	0.072
Least 2nd	Angola	0.032	Saudi Arabia	0.163	Colombia	0.184	Indonesia	0.1
Least 3rd	US	0.037	Angola	0.176	Indonesia	0.191	Angola	0.126

Solely looking at the CI scores of the supplier countries makes it difficult to provide us with a full perspective on the crude oil import supply chain of refineries in China. More analysis is conducted in the next section.

4.3.3 Four-Sector Analysis of CI Scores and Quantity of Imports

In this part, a four-sector analysis is conducted based on the CI scores and quantity of imports. In order to find out if there is any trend in relation with geographical regions, we categorized all the supplier countries into their geographical regions, which is slightly different from the regions of routes described in the section of data collection. The classification of the supplier countries based on their geographical locations is shown in Table 4.3-5.

Table 4.3- 5 Classification of the supplier countries based on their geographical locations

Regions	*Countries*
Africa	Angola
	Congo, Republic of
	Equatorial Guinea
	Gabon
	Ghana
	Libya
	South Sudan
Oceania & Asia	Australia
	Indonesia
	Malaysia
	Russian Federation
	Vietnam
Europe	United Kingdom
Middle East	Iran, Islamic Republic of
	Iraq
	Kuwait
	Oman
	Saudi Arabia
	United Arab Emirates
North & South America	Brazil
	Colombia
	United States of America
	Venezuela

Based on the categorization, an illustrative chart of CI scores and quantity of imports from each supplier country is shown below (Chart 4.3-3 (1) to (4)). The reason of incorporating the import quantity is that the more imports from a certain country or region, the more vulnerability the importer's supply chain carries. In Chart 4.3-3 (1) to (4), the horizontal axis represents the quantity of imports in units of tonnes, and the vertical axis states different levels of CI scores. Different colors of dots are used to distinguish countries. The dashed orange line in the chart signals the average value of the CI scores. The vertical dashed blue line marks the average quantity of imports in each year. The dashed lines segment the area into four sectors: the upper-right corner is sector I, the upper-left corner is sector II, the lower-left corner is sector III, and the lower-right corner is sector IV. In sector I are the countries with high CI scores and large amount of crude oil exportation to China represented by a color dot; in sector II are the ones with high CI scores and relatively low amount of oil exportation to China; in sector III are the suppliers with low CI scores and relatively low amount of oil exports to China; and in sector IV are the ones with low CI scores but large quantity of crude oil exports to China.

Chart 4.3-3 (1) CI scores and quantity of imports from each supplier country in 2015

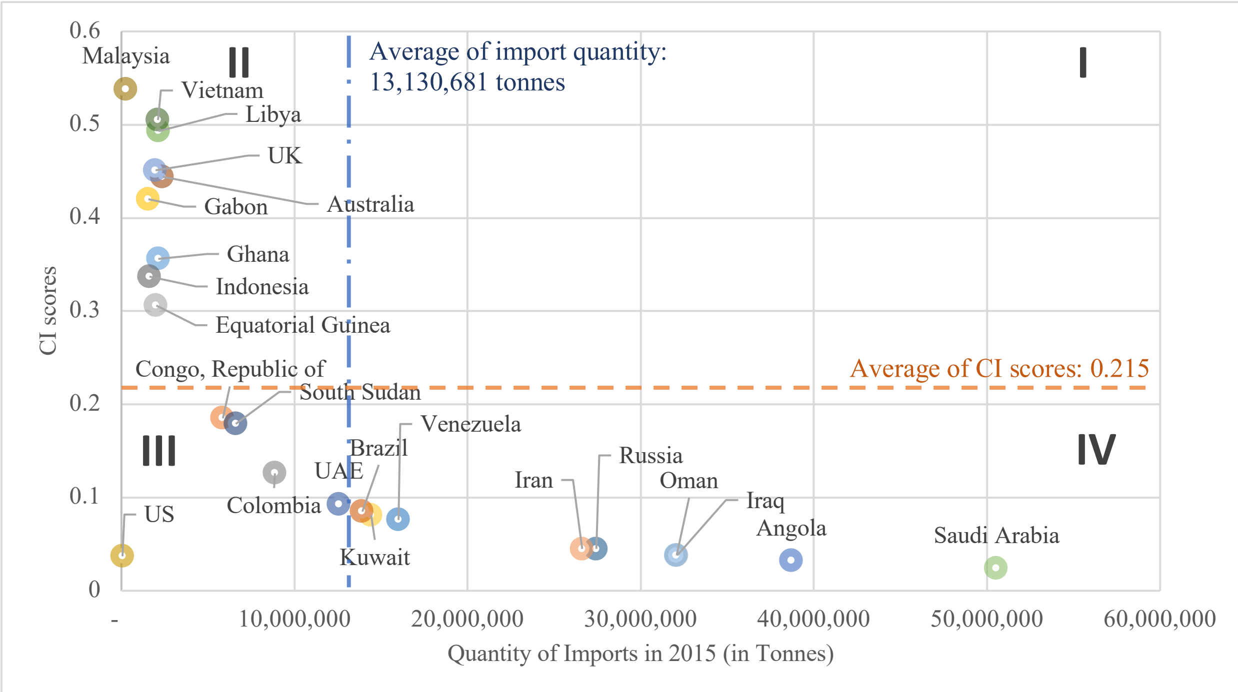


Chart 4.3-3 (2) CI scores and quantity of imports from each supplier country in 2016

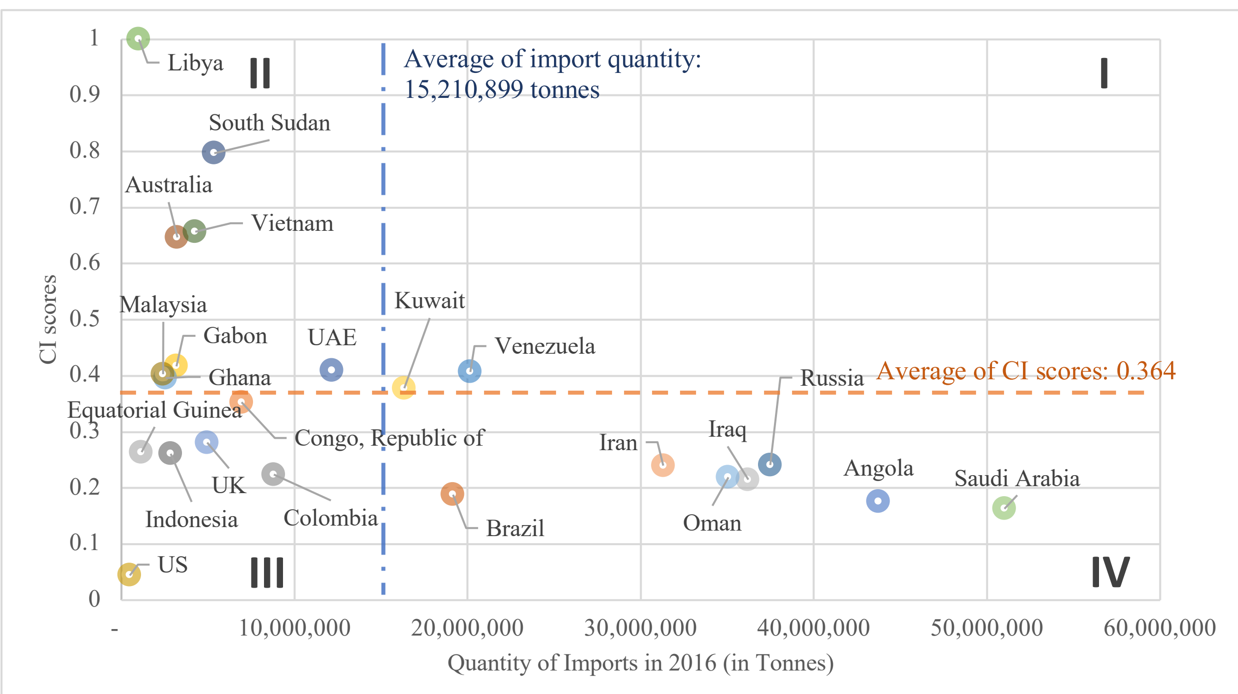


Chart 4.3-3 (3) CI scores and quantity of imports from each supplier country in 2017

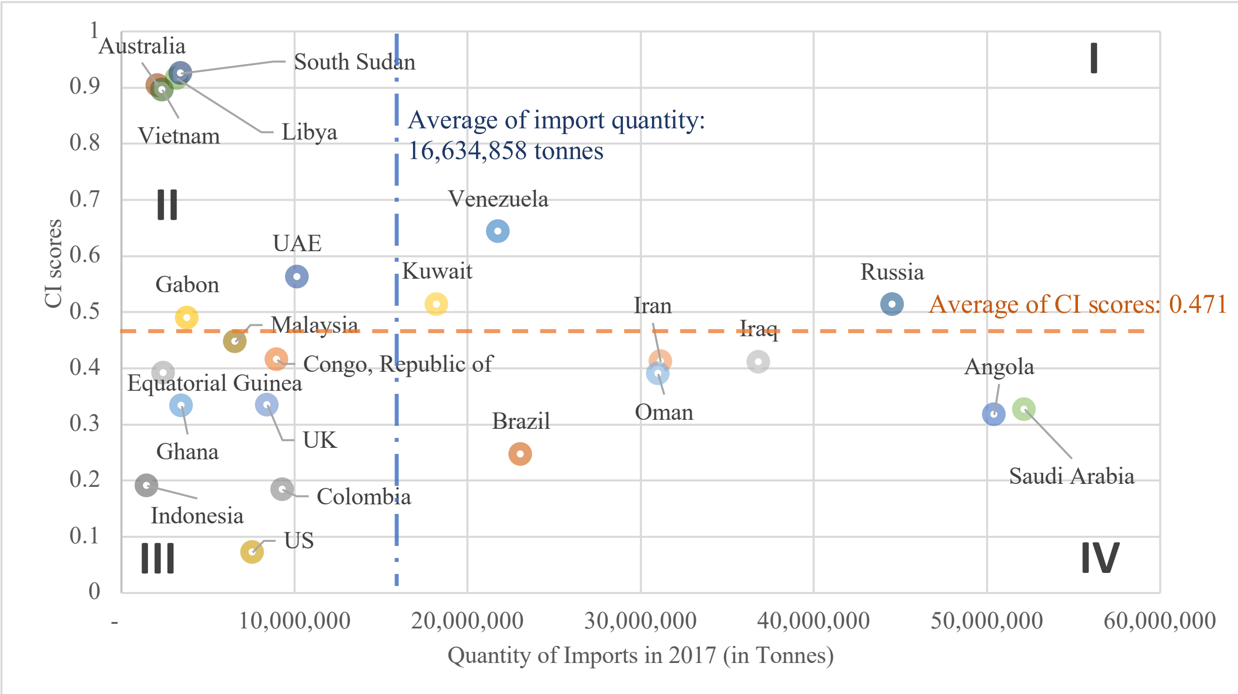
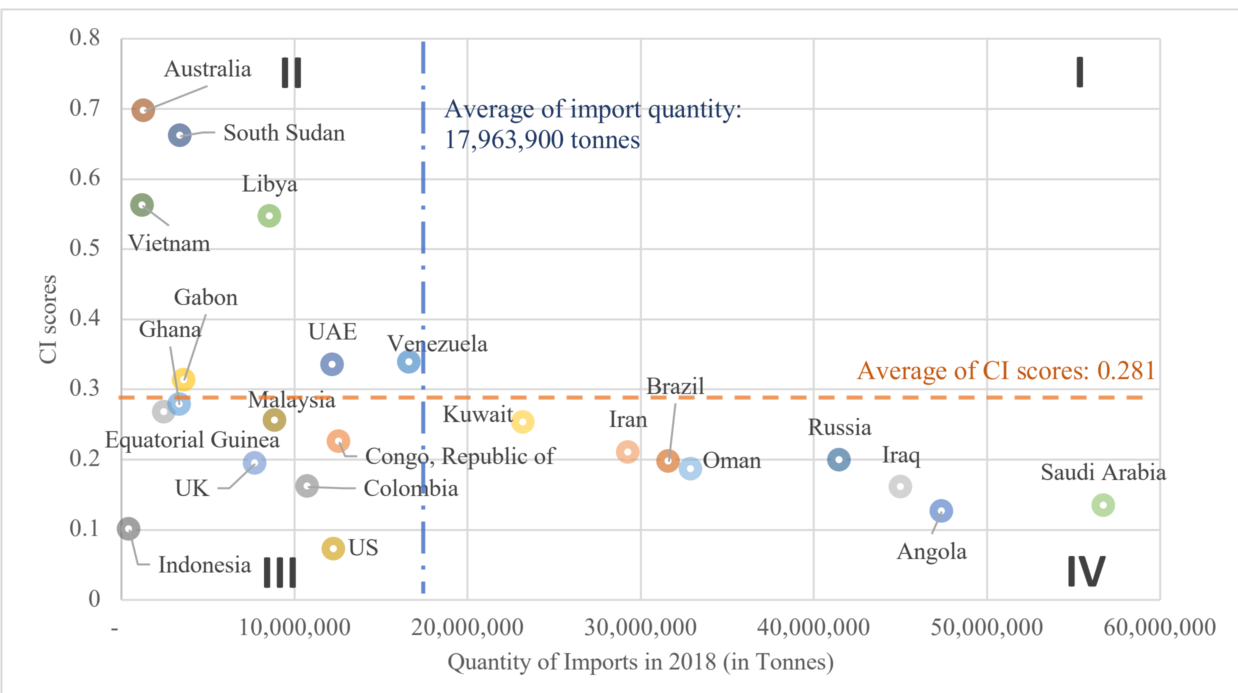


Chart 4.3-3 (4) CI scores and quantity of imports from each supplier country in 2018



In Chart 4.3-3 (1) to (4), most countries cluster in sector II, III and IV. There are only three countries in 2017 in Chart 4.3-3 (3) that appear in sector I.

The most alerting supplier countries to refineries are the ones in sector IV, because the oil supply quantity from those countries is significant, whereas those countries have rather low level of safety and reliability. As can be seen from the above charts and Table 4.3-6 below, from 2015 to 2018, sector-IV countries comprise 75.06%, 66.65%, 53.56% and 66.61% of all crude oil imports to China respectively. To be specific, one African country, Angola, occurs four times in sector IV; four Middle East countries in 2015 and 2018 and five Middle East countries in 2016 and 2017 can be found in sector IV; Russia, whose port locates in Asia, presents three times in sector IV except in year 2017; Brazil appears four times in sector IV, and another South American country, Venezuela, is in sector IV in 2015. Among those countries, the ones in Middle East occupy the largest portion, taking 46.43%, 40.31%, 36.04% and 40.52% of total imports from 2015 to 2018 accordingly. The imports of refineries are highly concentrated in one region, which is the Middle East. Middle East is the largest crude oil export region worldwide, it is inevitable to import significant amount of crude oil from that area. However, the escalating tension between Iran and other countries lately has greatly threatened the security of transportation in the Hormuz Strait. The sanction imposed by the US to Iran as well as the recent armed attack on oil fields and infrastructure in Saudi Arabia intensified uncertainty on stable crude oil supply from this area. Due to the unexpected attack on Saudi's oil fields, the crude oil markets, both Brent and WTI, have witnessed the biggest surge in oil price during the past three decades, according to Bloomberg[10].

[10] Bloomberg "Oil Prices Jump Most on Record After Saudi Arabia Strike" (Last date of access: September 20, 2019): https://www.bloomberg.com/news/articles/2019-09-15/oil-prices-jump-19-after-attack-cuts-saudi-arabian-supplies

Freight rates of tankers from this region was propped up due to less supply of fuel oil for the tankers. The soaring oil prices and freight rates noticeably affected the importing costs of crude oil for the refineries in China. When classifying grades of crudes, the ones with similar levels of density and sulfur content can be regarded as substitutes for each other. Crude oil from the Middle East has few substitutes due to its unique grade, leading to a more severe situation for the refineries.

Table 4.3- 6 CI scores and percentage of oil imports of countries in sector IV

Year 2015	***Africa***	***Asia***	***Middle East***					***South America***	
Countries	Angola	Russia	Iran	Iraq	Kuwait	Oman	Saudi Arabia	Brazil	Venezuela
CI scores	0.032	0.045	0.045	0.038	0.081	0.038	0.024	0.085	0.076
Oil imports (%)	11.53%	8.18%	7.93%	9.57%	4.30%	9.56%	15.07%	4.15%	4.77%

Year 2016	***Africa***	***Asia***	***Middle East***				***South America***
Countries	Angola	Russia	Iran	Iraq	Oman	Saudi Arabia	Brazil
CI scores	0.176	0.241	0.240	0.215	0.219	0.163	0.188
Oil imports (%)	11.48%	9.84%	8.21%	9.50%	9.20%	13.39%	5.03%

Year 2017	***Africa***	***Middle East***				***South America***
Countries	Angola	Iran	Iraq	Oman	Saudi Arabia	Brazil
CI scores	0.317	0.412	0.411	0.390	0.327	0.247
Oil imports (%)	12.02%	7.43%	8.78%	7.39%	12.44%	5.50%

Year 2018	***Africa***	***Asia***	***Middle East***					***South America***
Countries	Angola	Russia	Iran	Iraq	Kuwait	Oman	Saudi Arabia	Brazil
CI scores	0.126	0.199	0.21	0.16	0.252	0.186	0.134	0.197
Oil imports (%)	10.26%	8.98%	6.34%	9.75%	5.03%	7.12%	12.28%	6.85%

Another alert should arise for Angola, from which China imports the second largest amount of crude oil, despite its rather low CI scores. The reason behind the massive imports from Angola is that the oil companies in China established long-term corporation relationship with the multi-national oil firms in Angola, enabling stable and sufficient amount of supply. However, due to depletion of oil fields and decreasing foreign investment in Angola, it is facing a huge challenge of potential decline in oil production after 2019. Hence, decision makers in refineries should be more prudent in deciding whether to continue cooperation or import in large amount from this country.

Apparently, the refineries have realized the negative impact of highly concentrated suppliers and therefore they gradually reduced the proportion of crude oil imports from both Angola and Saudi Arabia, so as from Oman, from 2015 to 2018. Russian is an exception. The percentage of imports first increased from 2015 to 2017, then dropped slightly in 2018. The decline in imports share only represents the crude oil transported by tankers, which is one of the two transportation modes to import Russian crudes to China. The other one is via China-Russia pipelines. If the pipeline-transported crude oil is included, the proportion of crudes imported from Russia presents a continuous upward trend from 2015 to 2018, since the imported crude oil via the pipelines gradually replaces the one via marine transportation. Reasons behind the expanding quantity of imports from Russia are China-Russia bilateral agreement on energy trades, construction and utilization of pipelines and geographical adjacency from Russian oil ports to destination in China. The agreement between two countries secures a stable supply of crude oil. Nonetheless, the impact can be revertible. Excessive reliance on a single supplier can be venturesome and risky, and maintaining such relation may result in great costs. Pipeline transportation greatly reduces uncertainty en route, including congestion at busy chokepoints, piracy attacks and disturbance caused by weather, fluctuation of maritime freight rate and tanker rent, etc. However, pipeline transportation is still subject to vandalism and high installation and maintenance expense, which is outside the control of a single refinery. Geographical adjacency generates more flexibility of marine transportation. Since longer route distance means more time consumed in voyage and greater chance of being exposed to uncertainty, a short travel distance indicates less lead time, allowing a refinery to react more quickly to demands from its downstream. The distance from Vladivostok port in Russia to Qingdao port is 1001 nm. If an oil tanker travels in a constant and economical speed of 13.5 knots per hour, 24 hours per day, it takes only 3 days for an oil tanker to arrive.

Quantity of imports from Brazil continues to increase, mainly because of its burgeoning crude oil production due to installing and using new floating production storage and offloading solutions to drill oil from pre-salt oil fields in sea. Crude oil from Brazil has a grade of medium density and low sulfur, which share similar characteristics with crudes from west Africa and Russia. Therefore, Brazilian crude oil can be substitutes for Russian oil and Angolan oil, as well as Libyan oil. It provides a buffer to the crude oil import supply chain of refineries in China. When a similar grade of oil from a specific supplier is insufficient or no longer available, demand can be filled by oil from other supplier countries.

In the four-sector charts, sector III indicates a moderate risk level, since the low quantity of imports is unlikely to cause serious damage to the import supply chain of Chinese refineries, even though the CI scores are low for countries in this sector. Decision makers should be cautious about the countries at the dividing point between sectors III and IV, because those counties may oscillate between the two sectors when the import amount from those countries increases. As shown in Table 4.3-7, there are five countries in sector III in 2015, accounting for 10.12% of total crude imports in that year. Two of them are African countries, Republic of Congo and South Sudan; one is United Arab Emirates in the Middle East; and two of them are American countries, Colombia and the US. The number of countries increases to six in 2016, but the percentage of oil imports drops to 6.61%. The countries are Republic of Congo and Equatorial Guinea from Africa, Indonesia from Asia, the UK from Europe and, Colombia and the US from North and South

America. In 2017, eight countries show up in the sector III. Ghana from Africa and Malaysia from Asia are two countries newly appear in sector III in 2017, beside the countries in 2016 as mentioned above. The percentage of imports from those countries inflates to 11.52% in 2017. Countries in sector III in 2018 are the same as in 2017, and the percentage of imports slightly raises to 12.67%. Most countries are from Africa, Asia, North and South America.

For most west African countries, petroleum industry acts as a pillar to the national economy. Their governments heavily rely on revenues from crude oil exportation. Proved oil reserves and production in this region keep growing because of innovations on excavating technology and extracting crudes from floating platforms in the offshore area. However, political upheaval and frequent piracy activities in this region threaten stability of crude oil supply. Furthermore, excessive dependence on revenue of oil exportation makes the west African countries greatly exposed to fluctuations of crude oil price. Given the oil prices are becoming more unpredictable and volatile in recent years, oscillating fiscal income affects further investment on current and new crude oil excavation projects and infrastructure, slowing the economic growth and causing instability in providing sufficient crude oil. Besides, countries such as Equatorial Guinea and Angola are gradually shifting their focus from maturing oil production to emerging natural gas excavation. One can expect declining supply from those countries in the future.

Table 4.3- 7 CI scores and percentage of oil imports of countries in sector III

Year 2015	*Africa*		*Middle East*	*North & South America*				
Countries	Congo, Republic of	South Sudan	UAE	Colombia	US			
CI scores	0.185	0.179	0.093	0.126	0.037			
Oil imports (%)	1.75%	1.97%	3.75%	2.64%	0.02%			
Year 2016	***Africa***		***Asia***	***Europe***	***North & South America***			
Countries	Congo, Republic of	Equatorial Guinea	Indonesia	UK	Colombia	US		
CI scores	0.353	0.264	0.261	0.281	0.224	0.044		
Oil imports (%)	1.82%	0.31%	0.75%	1.30%	2.31%	0.13%		
Year 2017	***Africa***			***Asia***		***Europe***	***North & South America***	
Countries	Congo, Republic of	Equatorial Guinea	Ghana	Indonesia	Malaysia	UK	Colombia	US
CI scores	0.415	0.391	0.333	0.191	0.447	0.335	0.184	0.072
Oil imports (%)	2.15%	0.58%	0.83%	0.35%	1.57%	2.01%	2.22%	1.81%
Year 2018	***Africa***			***Asia***		***Europe***	***North & South America***	
Countries	Congo, Republic of	Equatorial Guinea	Ghana	Indonesia	Malaysia	UK	Colombia	US
CI scores	0.225	0.267	0.278	0.1	0.255	0.194	0.161	0.072
Oil imports (%)	2.72%	0.54%	0.73%	0.10%	1.92%	1.67%	2.33%	2.66%

Indonesia and Malaysia used to be two main oil producers in southeastern Asia. They were advantageous crude oil providers to Chinese refineries not only because of the short distance between them and China, but also owing to the medium density and very low sulfur content of their crude oil as well as rich in paraffin, making it one of the best-quality crude oil worldwide. However, due to depletion of resources and surging domestic demand on natural resource, Indonesia, the erstwhile only OPEC member in southeastern Asia, had to reduce the amount of exportation to support domestic development, and left OPEC in 2009 for the first time and then again in 2016[11]. Though Malaysia has experienced dwindling production in old oil fields, it initiated new projects to detect other oil fields and managed to sustain stable production. Another noticeable feature of these two countries is that they both encompass the most important marine channel, the Straits of Malacca, for Chinese oil importers. As mentioned in the previous sections, over 80% of all imports in China each year transited through the Strait of Malacca, from 2015 to

[11] OPEC, "Member Countries" (Last date of access: September 24, 2019): https://www.opec.org/opec_web/en/about_us/25.htm

2018. With such massive reliance on a single chokepoint, the transportation risk escalates since once the Strait of Malacca is shut down, the costs and lost can be enormous.

As can be seen from Table 4.3-7, percentage of imports from Colombia remains stable in the four years of study, while the amount of imports from the US has enlarged by almost 200 times from 2015 to 2018. In 2015, the US lifted its export ban on crude oil since last century, and since then China started to import crudes from the US. In addition to that, the innovative techniques on drilling shale oil prompted the ramp-up crude oil production and exportation in US, transforming the US from a net oil importer to a net exporter in 2018 for the first time in last 75 years, according to Bloomberg[12]. Its shale oil has characteristics of light density and low sulfur content, which is a substitute to the Brent crude oil in UK and other North Sea crudes. It can be processed and refined in most Chinese refineries, with a lower price compared with the Brent crude oil. However, the trade war between China and the US, which started in late 2018, greatly increases uncertainty and risks of crude oil import supply chain for the Chinese refiners, due to unsure punitive tariffs that China customs may impose to the imported US crude oil. Before the trade war, crude oil from the US was free of tariffs, meaning that the deteriorated relationship between the two countries could sharply boost purchase costs for the refiners. As a consequence, the imports of US oil dropped acutely from 16,890 thousand barrels in July 2018 to 4,035 thousand barrels in August 2018[13]. Although the import quantity started to rebound in May 2019, prospect of the bilateral relationship is still unclear, since announcements and policies from both sides are leading back and forth

[12] Bloomberg, "The U.S. Just Became a Net Oil Exporter for the First Time in 75 Years" (Last date of access: September 24, 2019): https://www.bloomberg.com/news/articles/2018-12-06/u-s-becomes-a-net-oil-exporter-for-the-first-time-in-75-years

[13] Data from the U.S. Energy Information Administration (EIA), "U.S. Exports to China of Crude Oil and Petroleum Products" (Last date of access: September 24, 2019): https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=MTTEXCH1&f=M

movement of the trade war. Moreover, voyaging from the Gulf coast of US to Qingdao is on the longest route compared to from other suppliers. It takes an oil tanker 54 days under the economical speed as discussed earlier. If weather en route is not suitable for sailing, length of the trip can be prolonged to over two months. Longer distance and voyaging time indicate longer time to respond to changes in demands for the importers, as well as more uncertainty may emerge along the route. The unit freight rate is also the highest among all routes, due to the longest distance among all.

Table 4.3- 8 CI scores and percentage of oil imports of countries in sector II

Year 2015	*Africa*				*Oceania and Asia*				*Europe*
Countries	Equatorial Guinea	Gabon	Ghana	Libya	Australia	Indonesia	Malaysia	Vietnam	UK
CI scores	0.306	0.420	0.356	0.493	0.444	0.337	0.538	0.505	0.451
Oil imports (%)	0.60%	0.46%	0.64%	0.64%	0.71%	0.48%	0.08%	0.63%	0.59%
Year 2016	***Africa***				**Oceania and Asia**			***Middle East***	
Countries	Gabon	Ghana	Libya	South Sudan	Australia	Malaysia	Vietnam	UAE	
CI scores	0.417	0.396	1	0.797	0.647	0.403	0.657	0.409	
Oil imports (%)	0.83%	0.67%	0.27%	1.41%	0.85%	0.63%	1.12%	3.20%	
Year 2017	***Africa***			**Oceania and Asia**		***Middle East***			
Countries	Gabon	Libya	South Sudan	Australia	Vietnam	UAE			
CI scores	0.490	0.916	0.925	0.904	0.896	0.563			
Oil imports (%)	0.91%	0.77%	0.82%	0.50%	0.56%	2.42%			
Year 2018	***Africa***			**Oceania and Asia**		***Middle East***	***North & South America***		
Countries	Gabon	Libya	South Sudan	Australia	Vietnam	UAE	Venezuela		
CI scores	0.313	0.546	0.661	0.697	0.562	0.335	0.338		
Oil imports (%)	0.78%	1.86%	0.73%	0.28%	0.26%	2.64%	3.60%		

Countries in sector II are the ones with least risks, since they have high CI scores and rather low exports quantity to China, leaving little risk even if their CI scores should deteriorate and move to sector III. As shown in Table 4.3-8, most of the countries are from Africa, Oceania and Asia. Similar to Angola and other African countries, petroleum industry plays as the most important pillar to domestic economy. Though sharing resembling quality as Angolan oil, import quantity from the African countries in sector II is nowhere near that of Angolan oil. There can be more chances for diversification of oil sources in this area. Oceanian and Asian countries are given advantages of rather short distance and stable political and economic environment, however, because of depletion of natural resource and growing domestic demand for crude oil, those countries gradually reduce amount of exportation and become net importers, enforcing Chinese refiners to steer to other sustainable suppliers.

Table 4.3- 9 CI scores and percentage of oil imports of countries in sector I

Year 2016	*Middle East*	*South America*	
Countries	Kuwait	Venezuela	
CI scores	0.378	0.407	
Oil imports (%)	4.29%	5.29%	
Year 2017	***Asia***	***Middle East***	***South America***
Countries	Russia	Kuwait	Venezuela
CI scores	0.513	0.514	0.643
Oil imports (%)	10.62%	4.35%	5.19%

There are two countries, Kuwait form Middle East and Venezuela from South America, in sector I in 2016. Then in 2017, apart from the two countries in 2016, Russia appears in this echelon. The refineries should pay much attention to the countries in sector I, because although with high CI scores, those countries can fall directly to sector IV when their CI scores worsen. In fact, those countries are too close to the dividing line of sector IV and sector I. Kuwait and Russia are in sector IV in years when they are not in sector I, and Venezuela is in sector IV in 2015 and in sector II in 2018. Among all supplier countries, Venezuela has the largest proven crude oil reserve worldwide of 47 billion tonnes. With its production and export level in 2015, Venezuela has a potential oil export ability of 253 years. However, its production and exportation level keep shrinking, due to sanction imposed by the US and its own domestic turmoil. Thus, the source of supply is difficult to be guaranteed. Decision makers in refineries should be aware of the risk of inadequate supply from Venezuela. Kuwait has a proved reserve of 14 billion tonnes, which ranks number sixth among all supplier countries. Its production level stabilizes at 148 million tonnes per year on average, and its exportation amount remains steady around 101.9 million tonnes per year on average. Nonetheless, as a member country of the Organization of the Petroleum Exporting Countries (OPEC), Kuwait has to respond to the OPEC's pact of cutting crude oil production, which is extended to March 2020[14], in order to prop up the sliding oil price due to the US crudes flooding into the market. Under this situation, expectation on the future crude oil supply would be lessened not only from Kuwait, but also from other OPEC countries, including Algeria, Angola, Congo, Ecuador, Equatorial Guinea, Gabon, Iran, Iraq, Libya, Nigeria, Saudi Arabia, United Arab Emirates (UAE) and Venezuela.

[14] Reuters, "OPEC posts first 2019 oil-output rise despite Saudi cuts: Reuters survey" (Last date of access: September 26, 2019): https://www.reuters.com/article/us-oil-opec-survey/opec-posts-first-2019-oil-output-rise-despite-saudi-cuts-reuters-survey-idUSKCN1VK1YD

5. Suggestions to Decision Makers of Chinese Refineries

As aforementioned, refineries in China face different extent of risks under the increasingly turbulent political and economic environment. As the geopolitical risks are worsening and supply of crude oil is becoming more unstable, decision makers in Chinese refineries are advised to plan ahead for possible risks and uncertainties, with regard to strengthening the security level of their crude oil import supply chain. Based on the risks in previous parts, suggestions are provided as listed below.

First of all, refineries need to import crudes from more diversified sources. Currently, the source of supply mainly concentrates on a single region (Middle East and Africa) and several countries (Saudi Arabia, Angola and Russia), which would cause disturbance easily to the crude oil import supply chain of the Chinese refineries. Therefore, the level of diversification should be improved further, not only by increasing the number of small suppliers, but also by reducing the import quantity of the large suppliers with high risks and looking for substitutive sources for them. Supplier countries such as Canada and Mexico are political-stable countries with large quantity of oil reserve, production and exportation. The source of suppliers can be expanded to those countries that are stable and rich in oil yet are still small suppliers of China. Additional costs, such as initial research and development costs, related banking and financial costs, related taxes and subsidies of certain countries, and opportunity costs of previous main suppliers, may emerge when refineries extend their sources of supply. However, for the purpose of assuring import security, those costs should be perceived in a long term.

Substitution of crudes with similar grades should be considered when importing crude oil. There are multiple sources of crudes with similar characteristics that can be treated as of same grades. For instance, crude oil from west African share similar grades with Russian oil and Brazilian oil, which is of medium density and low sulfur content; the US WTI has resembling characteristic to the UK Brent and oil from North Sea region, which is of light density and low sulfur; Mexican crude oil is of heavy density and high sulfur content, and Canadian oil sand shares the similar quality. For the grades of oil that have few substitutes, refiners are suggested to upgrade their refining equipment and technique for a wider range of petroleum products and higher quality of products. Nonetheless, since refining crude oil involves intensive capital investment, upgrading equipment can be very expensive and complex. For instance, if a refinery decides to upgrade a piece of distillation equipment for fewer sulfur content, the refinery not only needs to upgrade the desulfurization device, ahead of that, the refinery also needs to upgrade the hydrogenation device. It may consume hundreds of millions of US dollars, as well as several months of shutdown[15].

Signing long-term contracts with national oil companies in the oil rich countries is another method to secure the crude oil supply. When the oil supply is disturbed by unexpected events, demand of importers with long-term contracts will be filled ahead of other buyers without a long-term contract.

On the transportation stage, there are limited changes that the refineries can do to improve the transportation security. Analogously, refiners can sign long-term contracts with tanker leasing companies to assure stable freight rate and available vessels under emergency situations.

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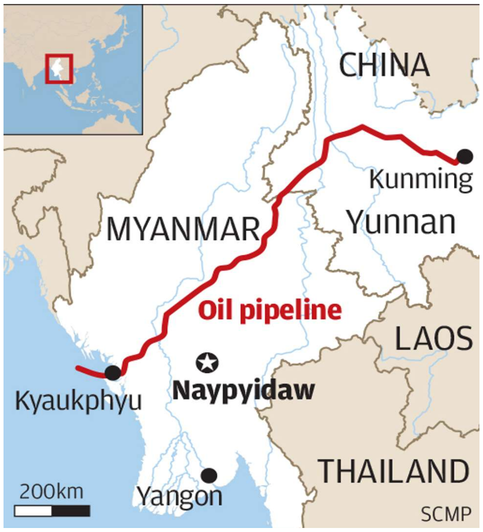
[15] Reuters, "Refiners Struggle as Low Sulphur Upgrade Costs Approach $1 Billion per Plant" " (Last date of access: October 6, 2019): https://gcaptain.com/refiners-struggle-as-low-sulphur-upgrade-costs-approach-1-billion-per-plant/

A bigger problem is that approximately 90% of all imported crude oil in China is transported via marine transportation, while over 80% of the tanker-carried crudes sail through the Straits of Malacca, including the imports from large suppliers. The locations of supplier countries determine that marine transportation is the most economical and feasible transportation mode, and pipeline is only suitable for adjacent countries. However, on national level, there are several agreements and contracts signed by Chinese government with neighbor countries that may change the so-called "Malacca dilemma". One of the contracts is the Sino-Myanmar crude oil pipeline, which is designed to start from Kyaukphya port in Myanmar to Kunming in Yunnan province in China (see Figure 5-1). In this way, crude oil imported from the Middle East, Africa and Europe is able to avoid going via the Straits of Malacca. The planned maximum capacity of this pipeline is 22 million tonnes per year[16], accounting for approximately 5 percent of total annual imports of crude oil to China. This pipeline has already been put into use in 2017. Another shortcut is a port-rail network between China and Pakistan, which is called "China–Pakistan Economic Corridor" project. The project starts from Gwadar port in Pakistan alongside the Arabian Sea, and its destination is in Kashgar, Xinjiang province, in northwest China (see Figure 5-2). The Gwadar port and Kashgar are connected by railway, providing an alternative transportation mode that can detour from the Straits of Malacca, for the crude oil tankers from the Middle East, Africa and Europe. This project is still under construction.

[16] South China Morning Post, "Myanmar pipeline gives China faster supply of oil from Middle East" (Last date of access: September 27, 2019): https://www.scmp.com/news/china/economy/article/2086837/myanmar-pipeline-gives-china-faster-supply-oil-middle-east

Figure 5- 1 Map of Sino-Myanmar crude oil pipeline



Source: South China Morning Post

Figure 5- 2 Map of China–Pakistan Economic Corridor

Source: BBC News

To overcome negative impact of freight rates volatility and crude oil prices fluctuation, refineries should extend their business to paper trading, in addition to the physical trading of crude oil. Since the transportation delay usually takes a month on average and the time required for other paperwork that need to be negotiated between buyers and sellers, refiners often import crudes two months ahead of time of discharging at destination ports. Applying financial derivative instruments such as crude oil options and futures to hedge against unwanted uncertainties can help the refineries to avoid potential loss due to oscillation of freight rates and oil prices.

An information sharing system is advised to be built up among Chinese refineries. If all refineries import at their maximum refining capacity during the same period, the quantity of crude oil required can be substantial. It may lead to a tight market with short supply and may even prop up the price of crude oil. With an information sharing system, refineries are able to plan ahead when to shut for maintenance and when to import crudes in a stagger.

6. Conclusion

With annual imports of 461.91 million tonnes in 2018, China has exceeded the US and became the largest importer of crude oil worldwide. With such a huge quantity of imports, Chinese refineries are subject to numerous uncertainties and risks from their suppliers and with respect to transportation. The objective of this thesis was to identify risks in the crude oil import supply chain of refineries in China, and to discuss how do the risks affect those refineries.

To do so, a composite indicator (CI) system and a DEA-like model were proposed based on risk indicators on both supply stage and transportation stage. Political and economic risks of a supplier country, potential oil export indicator and dependency of each supplier were indicators chosen on the supply stage; multiplier of distance of a route, dependency of each route, probability of piracy attacks in a selected route and volatility of freight rate were the indicators on the transportation stage. After risk indicators on each stage were identified, three normalization methods were compared against each other. As a result, distance-to-the-group-leader normalization was employed, as it is a ratio-scale normalization method and it preserves the unit-invariance of the original indicators. Then, an aggregation method, which was a benefit-of-the-doubt model bearing characteristics of DEA, was presented. The model aimed at maximizing the overall CI scores of each country, which is the summation of weighted indicators, where the most favorable weights were chosen for each supplier country.

Related data of four years (year 2015 to year 2018) was collected and computed to generate indicators of each supplier country in all four years. In the preliminary analysis, each indicator is inspected individually. Africa is where the average country risk is the highest among all five regions, and Middle East is the region with the second highest average country risk. As for potential oil exportation ability of supplier countries, two countries from Africa (Libya and South Sudan) and one country from South America (Venezuela) show strong variation through the years in oil supply. In each year, Chinese refineries import the largest portion of crudes from Middle East, while amount of imports from Africa comes next. Tankers from South and Central American countries have to travel the longest distance to reach China. Tankers travel less from African countries than from American countries, but they still need to travel on a longer route than the ones from other regions. Investigation on dependency level of each chokepoint reveals that over 80% of annual crude imports need to be transported via the Straits of Malacca, and over 45% of annual crude imports travel through Hormuz Strait. Tankers that travel on the West and South Africa route (via Cape of Good Hope - Straits of Malacca - South China Sea) are under the highest possibility of piracy attacks, since they need to sail through both West Africa and South East Asia, which are the two piracy hotspots. Although the average rents of spot-chartered oil tankers are the highest in regions of America and Africa, yet the volatility of the rents is the highest in the Middle East.

Bearing the basic observations in mind, we incorporated the indicators into the composite indicator (CI) DEA-like model. Due to the fact that restrictions of indicator shares are difficult to be determined, we firstly applied no constraint on the indicator shares, and then five sets of constraints with various upper and lower bounds were implemented and compared. Results showed that under the constraining bounds of [0.05, 0.6], the CI scores of supplier countries are distinguished and ranked without overlap, entailing a clearer comparison among countries. The following four-sector analysis of CI scores and quantity of imports provided a more comprehensive understanding on risk levels of supplier countries, and also confirmed the observations in the preliminary analysis.

Results indicated that refineries in China confront a situation where their imports significantly rely on a single region (Middle East) and several countries (Russia and Angola), which have relatively low CI scores, indicating a high level of risk. It can be concerning, since unavailability from one or more supplier countries can trigger destructive impacts on supply security of the refineries. Some countries represent a moderate risk level, due to the low quantity of imports and low CI scores, making it less likely to cause serious damage to the import supply chain of Chinese refineries. Countries with high CI scores and low quantity of imports are the ones with the lowest level of risks. A few countries with high CI scores and high quantity of imports appear only in 2016 and 2017. Though with high CI scores in these two years, those countries are risky because they can easily downgrade to the worst scenario.

The decision makers of Chinese refineries were suggested to diversify their sources of imports, to substitute crude imports to the ones with similar grades, and to sign long-term supply contracts with suppliers to secure the stable oil supply. On the transportation stage, they were advised to sign contracts with tanker leasing companies, and to opt for alternate transportation modes. Applying financial derivative instruments to hedge against risks and building an information sharing system among refineries are two other suggestions provided.

The main limitation of this research is that subjectivity cannot be completely eliminated during the process of choosing upper and lower bounds for the DEA-like model, though six sets of bounds were implemented and experimented. In reality, the bounds are chosen by experts, who can contribute more perceptions based on their professional knowledge. In future studies, risks at loading and discharging ports, such as delays and congestion, can be considered. Moreover, incorporation of financial analysis can yield new insights on the risks and solutions.

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Appendices

Appendix A. List of Models and Formulations

1. Supply stage:

1) Political and economic risk of a supplier country:

   - $CR_{tj} = \frac{100}{(PR_{tj}+ER_{tj})/2}$

2) Potential oil export indicator:

   - $PE_{tj} = \frac{R_{tj}}{P_{tj}} \times \frac{EX_{tj}}{P_{tj}}$

3) Dependency on each supplier, based on the import volume:

   - $DS_{itj} = s_{itj} = \frac{IM_{itj}}{TIM_{it}}$

2. Transportation stage:

4) Multiplier of distance of a route:

   - $MulL_{rj} = \frac{L_{rj}}{L_{min}}$

5) Dependency of each chokepoint:

   - $DC_{ct} = \frac{IM_{ict}}{TIM_{it}}$

6) Dependency of each route:

   - $DC_{rt} = \frac{IM_{irt}}{TIM_{it}}$

7) Probability of piracy attacks in a selected route:

   - $P_{rt} = \sum_{c=1}^{n} p_{crt} \prod_{\substack{k=1 \\ k\neq c}}^{n} (1 - p_{krt})$

8) Volatility of freight rate:

- $VFR_{rtz} = \frac{1}{W-1} \sum_{\omega=1}^{W-1}(\log(\frac{FR_{rtz,\omega+1}}{FR_{rtz,\omega}}))^2$

3. **Normalization method:**

9) Min-Max normalization:

- $X_\gamma^* = \frac{x_\gamma - \min_{\varrho\in\Gamma}(x_\varrho)}{\max_{\varrho\in\Gamma}(x_\varrho) - \min_{\varrho\in\Gamma}(x_\varrho)}$

10) Z-score normalization:

- $X_\gamma^* = \frac{x_\gamma - \mu_\Gamma(x_\gamma)}{\sigma_\Gamma(x_\gamma)}$

11) Distance-to-the-group-leader:

- $X_\gamma^* = \begin{cases} \frac{x_\gamma}{\max_{\varrho\in\Gamma}(x_\varrho)}, & \text{(for } x_\gamma \text{ that is the larger the better)} \\ \frac{\min_{\varrho\in\Gamma}(x_\varrho)}{x_\gamma}, & \text{(for } x_\gamma \text{ that is the smaller the better)} \end{cases}$

12) Normalization of indicators on the supply stage:

- $X_{\gamma,tj}^* = \begin{cases} \frac{x_{\gamma,tj}}{\max_{j\in J}(x_{\gamma,tj})} \\ \frac{\min_{j\in J}(x_{\gamma,tj})}{x_{\gamma,tj}} \end{cases}$

13) Normalization of indicators on the transportation stage:

- $Y_{\gamma,rt}^* = \begin{cases} \frac{y_{\gamma,rt}}{\max_{r\in R}(y_{\gamma,rt})} \\ \frac{\min_{r\in R}(y_{\gamma,rt})}{y_{\gamma,rt}} \end{cases}$

4. **DEA-like model**

14) Cherchye, et al.'s model (2007):

- $CI_c = \max_{w_{c,\gamma}} \frac{\sum_{\gamma=1}^{\Gamma} w_{c,\gamma} x_{c,\gamma}}{\max_{\zeta\in\mathbb{C}} \sum_{\gamma=1}^{\Gamma} w_{c,\gamma} x_{\zeta,\gamma}}$

15) Linearized model of the above one:

- $CI_c = \max_{w_{c,\gamma}} \sum_{\gamma=1}^{\Gamma} w_{c,\gamma} x_{c,\gamma}$

16) Sum of all weighted indicators less than one:

- $\sum_{\gamma=1}^{\Gamma} w_{c,\gamma} x_{c,\gamma} \leq 1, \quad for\ each\ country\ c$

17) Non-negativity constraint of each weight:

- $w_{c,\gamma} \geq 0, \quad for\ each\ indicator\ \gamma$

18) Binding constraint of indicator shares:

- $\alpha_{\gamma} \leq \frac{w_{c,\gamma} x_{c,\gamma}}{\sum_{\gamma=1}^{\Gamma} w_{c,\gamma} x_{\mathbb{C},\gamma}} \leq \beta_{\gamma}$

Appendix B. Tables

Table B-1 Detailed data on major suppliers of China's crude oil import from 2015 to 2018

Exporters	***Year 2015***		***Year 2016***		***Year 2017***		***Year 2018***	
	Imported quantity, Tonnes	**% of year total**	**Imported quantity, Tonnes**	**% of year total**	**Imported quantity, Tonnes**	**% of year total**	**Imported quantity, Tonnes**	**% of year total**
*Russian Federation **	42,434,134	12.65%	52,478,386	13.77%	59,538,196	14.19%	71,494,428	15.48%
Saudi Arabia	50,554,948	15.07%	51,005,652	13.39%	52,179,521	12.44%	56,733,916	12.28%
Angola	38,693,935	11.53%	43,735,747	11.48%	50,416,004	12.02%	47,387,584	10.26%
Iraq	32,105,115	9.57%	36,211,685	9.50%	36,815,228	8.78%	45,044,468	9.75%
Oman	32,070,972	9.56%	35,061,494	9.20%	31,006,894	7.39%	32,909,748	7.12%
Brazil	13,918,942	4.15%	19,155,317	5.03%	23,090,321	5.50%	31,622,229	6.85%
Iran, Islamic Republic of	26,614,586	7.93%	31,297,675	8.21%	31,151,914	7.43%	29,272,656	6.34%
Kuwait	14,425,906	4.30%	16,339,072	4.29%	18,243,452	4.35%	23,212,383	5.03%
Venezuela	16,007,916	4.77%	20,154,171	5.29%	21,761,404	5.19%	16,634,552	3.60%
Congo, Republic of	5,863,193	1.75%	6,941,462	1.82%	9,002,728	2.15%	12,580,546	2.72%
United States of America	62,290	0.02%	485,433	0.13%	7,580,683	1.81%	12,281,297	2.66%
United Arab Emirates	12,565,437	3.75%	12,181,703	3.20%	10,157,654	2.42%	12,199,161	2.64%
Colombia	8,867,436	2.64%	8,805,098	2.31%	9,302,980	2.22%	10,768,491	2.33%
Malaysia	270,365	0.08%	2,407,954	0.63%	6,587,311	1.57%	8,882,712	1.92%
Libya	2,146,791	0.64%	1,015,563	0.27%	3,220,459	0.77%	8,570,213	1.86%
United Kingdom	1,973,047	0.59%	4,954,619	1.30%	8,436,063	2.01%	7,725,501	1.67%
Gabon	1,558,341	0.46%	3,178,523	0.83%	3,808,903	0.91%	3,624,931	0.78%
South Sudan	6,605,683	1.97%	5,364,599	1.41%	3,432,740	0.82%	3,391,045	0.73%
Ghana	2,132,634	0.64%	2,560,477	0.67%	3,495,886	0.83%	3,355,999	0.73%
Equatorial Guinea	2,014,955	0.60%	1,166,821	0.31%	2,427,654	0.58%	2,479,774	0.54%
*Kazakhstan ***	4,991,019	1.49%	3,233,992	0.85%	2,502,102	0.60%	2,287,402	0.50%
Australia	2,388,751	0.71%	3,236,105	0.85%	2,100,070	0.50%	1,316,011	0.28%
Vietnam	2,114,860	0.63%	4,265,960	1.12%	2,360,431	0.56%	1,222,108	0.26%
Indonesia	1,615,433	0.48%	2,847,151	0.75%	1,485,246	0.35%	459,947	0.10%

** From 2015 to 2017, 15 million tonnes of crude oil imported from Russian Federation were transported via pipeline per year. From 2018, the quantity of crude oil transported via pipeline raise to 30 million tonnes per year. In our study, the portion of oil import via pipeline should be deducted from the total amount.*

*** All crude oil import from Kazakhstan are transported via pipeline, thus import from this country will not be considered in our study.*

Table B-2 Number of piracy attacks on tankers from 2015 to 2018

Regions	*Locations*	*2015*	*2016*	*2017*	*2018*
South East Asia	Indonesia	39	15	19	8
	Malacca Straits	4	0	0	0
	Malaysia	9	1	7	3
	Singapore Straits	1	0	2	1
South China Sea	China	0	1	0	0
	Philippines	5	5	6	4
	Vietnam	2	0	0	0
Indian Sub-Continent	Bangladesh	3	0	1	2
	India	10	9	1	4
South America (West)	Colombia	3	2	5	1
	Haiti	0	2	1	3
	Venezuela	0	3	9	9
South America (East)	Peru	0	4	0	0
West Africa	Angola	0	2	0	0
	Benin	0	0	0	4
	Dem. Republic of Congo	0	1	0	1
	Ghana	0	1	2	0
	Guinea	0	0	0	1
	Côte d'Ivoire	0	1	0	1
	Liberia	1	0	0	0
	Nigeria	7	27	16	25
	The Congo	1	0	0	3
	Togo	0	1	0	1
Red Sea	Gulf of Aden	0	0	1	1
	Red Sea	0	0	1	0
	Somalia	0	1	2	1
	Yemen	0	1	2	0
South and East Africa	Mozambique	0	1	0	2
	Kenya	2	2	1	0
	South Africa	0	1	0	0
Middle East	Oman	0	0	1	0
Total number of attacks		**87**	**81**	**77**	**75**

Table B-3 Breakdown of CI scores and indicator shares under various sets of weights (2015)

Supplier Countries	*Political and economic risk*	*Potential oil export*	*Dependency on each supplier*	*Multiplier of distance*	*Dependency of each route*	*Probability of piracy attacks*	*Volatility of freight rate*	*CI Scores*
Angola								
0.	0.5675	0.0363	0.0000	0.0000	0.0000	0.0000	0.0059	**0.610**
i.	0.5667	0.0364	0.0001	0.0001	0.0001	0.0001	0.0058	**0.609**
ii.	0.0998	0.0628	0.0013	0.0831	0.0013	0.0013	0.0013	**0.251**
iii.	0.0998	0.0628	0.0013	0.0831	0.0013	0.0013	0.0013	**0.251**
iv.	0.0016	0.0190	0.0016	0.0048	0.0016	0.0016	0.0016	**0.032**
v.	0.0063	0.0094	0.0016	0.0094	0.0016	0.0016	0.0016	**0.031**
Australia								
0.	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	**1.000**
i.	0.0066	0.0001	0.0001	0.0001	0.8895	0.0001	0.1036	**1.000**
ii.	0.2818	0.0157	0.0050	0.0050	0.6825	0.0050	0.0050	**1.000**
iii.	0.6000	0.0335	0.0050	0.0867	0.2648	0.0050	0.0050	**1.000**
iv.	0.0222	0.0534	0.0222	0.2121	0.0895	0.0222	0.0222	**0.444**
v.	0.0216	0.0512	0.0216	0.1295	0.1295	0.0567	0.0216	**0.432**
Brazil								
0.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	**1.000**
i.	0.0001	0.0003	0.0001	0.0254	0.0001	0.0001	0.9597	**0.986**
ii.	0.0024	0.0089	0.0024	0.0536	0.0024	0.0024	0.4123	**0.484**
iii.	0.0024	0.0058	0.0024	0.0437	0.1359	0.0024	0.2891	**0.482**
iv.	0.0042	0.0156	0.0042	0.0480	0.0042	0.0042	0.0042	**0.085**
v.	0.0042	0.0155	0.0042	0.0253	0.0056	0.0042	0.0253	**0.084**
Colombia								
0.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	**1.000**
i.	0.0001	0.0002	0.0001	0.0189	0.0001	0.0001	0.9680	**0.988**
ii.	0.0030	0.0075	0.0030	0.0350	0.0030	0.0030	0.5365	**0.591**
iii.	0.0029	0.0029	0.0029	0.0142	0.1768	0.0353	0.3525	**0.588**
iv.	0.0063	0.0160	0.0063	0.0540	0.0063	0.0063	0.0308	**0.126**
v.	0.0063	0.0160	0.0063	0.0378	0.0154	0.0378	0.0063	**0.126**
Congo, Republic of								
0.	0.5288	0.0312	0.0000	0.0000	0.0000	0.0000	0.0059	**0.566**
i.	0.5282	0.0312	0.0001	0.0001	0.0001	0.0001	0.0061	**0.566**
ii.	0.4102	0.0366	0.0025	0.0354	0.0025	0.0025	0.0025	**0.492**
iii.	0.2805	0.0289	0.0023	0.0299	0.0443	0.0023	0.0793	**0.467**
iv.	0.0138	0.0555	0.0093	0.0788	0.0093	0.0093	0.0093	**0.185**
v.	0.0360	0.0540	0.0090	0.0540	0.0090	0.0090	0.0090	**0.180**
Equatorial Guinea								
0.	0.3671	0.0093	0.0009	0.0232	0.0000	0.0000	0.0978	**0.498**
i.	0.3672	0.0093	0.0009	0.0231	0.0000	0.0000	0.0976	**0.498**
ii.	0.4003	0.0113	0.0024	0.0224	0.0024	0.0024	0.0410	**0.482**
iii.	0.2833	0.0085	0.0024	0.0217	0.0209	0.0024	0.1330	**0.472**
iv.	0.1834	0.0164	0.0153	0.0352	0.0248	0.0153	0.0153	**0.306**
v.	0.0865	0.0144	0.0160	0.0389	0.0316	0.0144	0.0865	**0.288**
Gabon								
0.	0.6868	0.0535	0.0019	0.0000	0.0000	0.0000	0.0000	**0.742**
i.	0.6862	0.0535	0.0019	0.0001	0.0001	0.0001	0.0001	**0.742**
ii.	0.6345	0.0542	0.0036	0.0138	0.0036	0.0036	0.0036	**0.717**
iii.	0.3662	0.0338	0.0031	0.0215	0.0233	0.0031	0.1595	**0.610**
iv.	0.2323	0.0722	0.0210	0.0318	0.0210	0.0210	0.0210	**0.420**
v.	0.1150	0.0590	0.0192	0.0317	0.0267	0.0192	0.1125	**0.383**

Ghana								
0.	0.7271	0.0347	0.0014	0.0000	0.0000	0.0000	0.0000	**0.763**
i.	0.7264	0.0347	0.0014	0.0001	0.0001	0.0001	0.0001	**0.763**
ii.	0.6422	0.0361	0.0036	0.0229	0.0036	0.0036	0.0036	**0.716**
iii.	0.3589	0.0225	0.0030	0.0213	0.0327	0.0030	0.1569	**0.598**
iv.	0.1930	0.0503	0.0178	0.0413	0.0178	0.0178	0.0178	**0.356**
v.	0.0988	0.0431	0.0165	0.0399	0.0254	0.0165	0.0893	**0.329**
Indonesia								
0.	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	**1.000**
i.	0.0001	0.0001	0.0001	0.0001	0.9988	0.0001	0.0001	**0.999**
ii.	0.1197	0.0048	0.0048	0.1217	0.6941	0.0048	0.0048	**0.955**
iii.	0.2316	0.0048	0.0048	0.0491	0.5711	0.0506	0.0399	**0.952**
iv.	0.0168	0.0168	0.0347	0.2019	0.0327	0.0168	0.0168	**0.337**
v.	0.0488	0.0163	0.0328	0.0980	0.0980	0.0163	0.0163	**0.327**
Iran, Islamic Republic of								
0.	0.5776	0.0695	0.0000	0.0000	0.0000	0.0561	0.0000	**0.703**
i.	0.5761	0.0695	0.0001	0.0001	0.0001	0.0562	0.0001	**0.702**
ii.	0.1043	0.1198	0.0018	0.1289	0.0018	0.0018	0.0018	**0.360**
iii.	0.1043	0.1198	0.0018	0.1289	0.0018	0.0018	0.0018	**0.360**
iv.	0.0023	0.0272	0.0023	0.0068	0.0023	0.0023	0.0023	**0.045**
v.	0.0022	0.0135	0.0022	0.0135	0.0022	0.0090	0.0022	**0.045**
Iraq								
0.	0.4681	0.1220	0.0000	0.0000	0.0000	0.0561	0.0000	**0.646**
i.	0.4669	0.1221	0.0001	0.0001	0.0001	0.0562	0.0001	**0.645**
ii.	0.0018	0.2318	0.0018	0.1201	0.0018	0.0018	0.0018	**0.361**
iii.	0.0018	0.2154	0.0018	0.1346	0.0018	0.0018	0.0018	**0.359**
iv.	0.0019	0.0226	0.0019	0.0057	0.0019	0.0019	0.0019	**0.038**
v.	0.0019	0.0112	0.0019	0.0112	0.0019	0.0075	0.0019	**0.037**
Kuwait								
0.	0.7217	0.1205	0.0000	0.0000	0.0000	0.0561	0.0000	**0.898**
i.	0.7198	0.1205	0.0001	0.0001	0.0001	0.0561	0.0001	**0.897**
ii.	0.2373	0.1900	0.0027	0.1081	0.0027	0.0027	0.0027	**0.546**
iii.	0.2373	0.1900	0.0027	0.1081	0.0027	0.0027	0.0027	**0.546**
iv.	0.0041	0.0488	0.0041	0.0122	0.0041	0.0041	0.0041	**0.081**
v.	0.0040	0.0241	0.0040	0.0241	0.0040	0.0161	0.0040	**0.080**
Libya								
0.	0.0000	0.7785	0.0000	0.0000	0.2215	0.0000	0.0000	**1.000**
i.	0.0001	0.7782	0.0001	0.0001	0.2213	0.0001	0.0001	**1.000**
ii.	0.0050	0.7667	0.0050	0.0050	0.2083	0.0050	0.0050	**1.000**
iii.	0.1406	0.6000	0.0050	0.0050	0.2394	0.0050	0.0050	**1.000**
iv.	0.0247	0.2960	0.0247	0.0247	0.0740	0.0247	0.0247	**0.493**
v.	0.0232	0.1392	0.0232	0.0917	0.1392	0.0232	0.0242	**0.464**
Malaysia								
0.	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	**1.000**
i.	0.0001	0.0001	0.0001	0.0001	0.9994	0.0001	0.0001	**1.000**
ii.	0.0050	0.0050	0.0542	0.1707	0.5826	0.0050	0.1775	**1.000**
iii.	0.0050	0.0050	0.0954	0.1659	0.4519	0.0050	0.2718	**1.000**
iv.	0.0269	0.0269	0.2008	0.2027	0.0269	0.0269	0.0269	**0.538**
v.	0.0263	0.0263	0.1576	0.1576	0.1051	0.0263	0.0263	**0.525**
Oman								
0.	0.6798	0.0235	0.0000	0.0000	0.0000	0.0561	0.0000	**0.759**
i.	0.6777	0.0235	0.0001	0.0001	0.0001	0.0562	0.0001	**0.758**
ii.	0.1129	0.0409	0.0015	0.1451	0.0015	0.0015	0.0015	**0.305**
iii.	0.1129	0.0409	0.0015	0.1451	0.0015	0.0015	0.0015	**0.305**

iv.	0.0019	0.0227	0.0019	0.0057	0.0019	0.0019	0.0019	**0.038**
v.	0.0019	0.0113	0.0019	0.0113	0.0019	0.0075	0.0019	**0.038**
Russia								
0.	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	**1.000**
i.	0.0001	0.0001	0.0001	0.0001	0.5648	0.4347	0.0001	**1.000**
ii.	0.0022	0.0445	0.0022	0.3844	0.0022	0.0022	0.0022	**0.440**
iii.	0.0022	0.0440	0.0022	0.2606	0.0022	0.1211	0.0022	**0.434**
iv.	0.0022	0.0270	0.0022	0.0067	0.0022	0.0022	0.0022	**0.045**
v.	0.0022	0.0135	0.0022	0.0135	0.0022	0.0090	0.0022	**0.045**
Saudi Arabia								
0.	0.7019	0.0781	0.0000	0.0000	0.0000	0.0561	0.0000	**0.836**
i.	0.6966	0.0790	0.0001	0.0059	0.0001	0.0491	0.0001	**0.831**
ii.	0.0012	0.1527	0.0012	0.0769	0.0012	0.0012	0.0012	**0.236**
iii.	0.0012	0.1408	0.0012	0.0880	0.0012	0.0012	0.0012	**0.235**
iv.	0.0012	0.0145	0.0012	0.0036	0.0012	0.0012	0.0012	**0.024**
v.	0.0012	0.0072	0.0012	0.0072	0.0012	0.0048	0.0012	**0.024**
South Sudan								
0.	0.0000	0.0000	0.0000	0.0000	0.8645	0.0000	0.1355	**1.000**
i.	0.0001	0.0001	0.0001	0.0025	0.8368	0.0001	0.1603	**1.000**
ii.	0.0047	0.0338	0.0047	0.0047	0.6733	0.0047	0.2059	**0.932**
iii.	0.0045	0.0489	0.0045	0.0319	0.5454	0.0518	0.2218	**0.909**
iv.	0.0089	0.1074	0.0089	0.0268	0.0089	0.0089	0.0089	**0.179**
v.	0.0088	0.0526	0.0088	0.0526	0.0351	0.0088	0.0088	**0.175**
United Arab Emirates								
0.	0.7683	0.0984	0.0000	0.0000	0.0000	0.0561	0.0000	**0.923**
i.	0.7662	0.0984	0.0001	0.0001	0.0001	0.0561	0.0001	**0.921**
ii.	0.3036	0.1492	0.0028	0.1051	0.0028	0.0028	0.0028	**0.569**
iii.	0.3036	0.1492	0.0028	0.1051	0.0028	0.0028	0.0028	**0.569**
iv.	0.0046	0.0556	0.0046	0.0139	0.0046	0.0046	0.0046	**0.093**
v.	0.0046	0.0274	0.0046	0.0274	0.0046	0.0183	0.0046	**0.091**
United Kingdom								
0.	0.0000	0.0000	0.0000	0.0000	0.8645	0.0000	0.1355	**1.000**
i.	0.9994	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	**1.000**
ii.	0.7102	0.0050	0.0050	0.0050	0.2133	0.0050	0.0565	**1.000**
iii.	0.6000	0.0050	0.0066	0.0050	0.3024	0.0050	0.0760	**1.000**
iv.	0.1643	0.0225	0.0225	0.0225	0.1739	0.0225	0.0225	**0.451**
v.	0.1329	0.0221	0.0225	0.0221	0.1329	0.0883	0.0221	**0.443**
United States of America								
0.	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	**1.000**
i.	0.0001	0.0001	0.9994	0.0001	0.0001	0.0001	0.0001	**1.000**
ii.	0.0019	0.0019	0.3621	0.0019	0.0019	0.0019	0.0019	**0.373**
iii.	0.1306	0.0017	0.2090	0.0017	0.0017	0.0017	0.0017	**0.348**
iv.	0.0056	0.0019	0.0224	0.0019	0.0019	0.0019	0.0019	**0.037**
v.	0.0111	0.0018	0.0111	0.0018	0.0074	0.0018	0.0018	**0.037**
Venezuela								
0.	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	**1.000**
i.	0.4986	0.5009	0.0001	0.0001	0.0001	0.0001	0.0001	**1.000**
ii.	0.0038	0.7372	0.0038	0.0038	0.0038	0.0038	0.0038	**0.760**
iii.	0.0030	0.3581	0.0030	0.0535	0.0030	0.0030	0.1733	**0.597**
iv.	0.0038	0.0454	0.0038	0.0113	0.0038	0.0038	0.0038	**0.076**
v.	0.0037	0.0222	0.0037	0.0222	0.0037	0.0148	0.0037	**0.074**
Vietnam								

0.	0.0000	0.0000	0.0000	0.2781	0.7219	0.0000	0.0000	**1.000**
i.	0.2951	0.0001	0.0001	0.1945	0.5100	0.0001	0.0001	**1.000**
ii.	0.0050	0.0050	0.0050	0.1593	0.8157	0.0050	0.0050	**1.000**
iii.	0.1381	0.0173	0.0050	0.2190	0.6000	0.0050	0.0157	**1.000**
iv.	0.0253	0.0476	0.0253	0.3031	0.0534	0.0253	0.0253	**0.505**
v.	0.0238	0.0442	0.0238	0.1427	0.1427	0.0748	0.0238	**0.476**

Table B-4 Number of binding constraints under each constraint (2015)

		Angola	*Australia*	*Brazil*	*Colombia*	*Congo, Republic of*	*Equatorial Guinea*	*Gabon*	*Ghana*	*Indonesia*	*Iran*	*Iraq*	*Kuwait*	*Libya*	*Malaysia*	*Oman*	*Russia*	*Saudi Arabia*	*South Sudan*	*United Arab Emirates*	*UK*	*USA*	*Venezuela*	*Vietnam*	***In Total***
i. Bigger than 0.0001	# of binding upper bound	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
	# of binding lower bound	4	1	4	4	4	2	4	4	5	4	4	4	3	0	4	4	3	2	4	5	0	3	3	**75**
ii. Bigger than 0.005	# of binding upper bound	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
	# of binding lower bound	4	4	4	4	4	3	4	4	4	4	5	4	2	1	4	5	5	4	4	4	6	6	4	**93**
iii. 0.005 to 0.6	# of binding upper bound	0	0	1	1	1	1	1	1	1	0	1	0	1	0	0	1	1	1	0	0	1	1	0	**14**
	# of binding lower bound	4	2	3	3	2	2	2	2	2	4	5	4	4	3	4	4	5	2	4	0	5	4	0	**70**
iv. 0.05 to 0.6	# of binding upper bound	1	0	0	0	0	1	0	0	1	1	1	1	1	0	1	1	1	1	1	0	1	1	1	**15**
	# of binding lower bound	5	4	5	4	4	3	4	4	4	5	5	5	5	5	5	5	5	5	5	5	5	5	4	**106**
v. 0.05 to 0.3	# of binding upper bound	2	2	1	1	2	2	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	**42**
	# of binding lower bound	4	3	2	3	4	2	2	2	3	4	4	4	3	4	4	4	4	4	4	3	4	3	3	**77**