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Assessment of Oil and Gas Supply Chain Management and Regional Differences in Efficiency: Application of Data Envelopment Analysis

By

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Abstract

Energy efficiency use and environmental protection have become crucial issues to achieve sustainable development as the utmost goal for all nations. The oil and gas industry is one of the primary energy sources in the world, and the industrialized market. Recently, the oil and gas industry has grown increasingly due to tighter environmental regulations, fierce competition and change of the demand patterns. Further, the industry has a considerable impact on the environment regarding its importance to the other industries as fuel for electricity generation, heating, transportations, and intermediate commodities. Although many renewable and sustainable energy initiatives aim to minimize the use of fossil fuel resources and reduce the environmental impacts of the oil and gas industry, this industry still plays an instrumental role in the current world energy system and provides the whole world by more than a half of its energy needs. The main aim of this thesis is to investigate the overall (environmental & operational) performance of the oil and gas industry's main segments by examining the exploring and production companies (upstream sector) and oil and gas refining companies (downstream sector). For that purpose, the Data Envelopment Analysis (DEA) approach is applied to assess the performance of the oil and gas supply chain sectors (upstream and downstream). For the upstream segment, DEA environmental models are utilized to investigate the unified efficiency in the US using 34 upstream oil and gas companies from 2011 to 2015. Besides, a combination of DEA and DEA-Discriminant Analysis is applied to investigate the oil and gas refineries' efficiency performance among four global regions over the period (2008-2017). Further, this research offers some recommended policies, which lead to enhancing O&G companies' efficiency performance to meet the environmental regulations and global market requirement.

PERFACE

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Chapter 1

Introduction

1.1 Background

Recently, efficient energy use and environmental protection have become essential issues to achieve sustainable development as the utmost goal for all nations. Sustainable development required enhancing the global life quality standard through the transfer of relevant technologies (e.g., electrification, transportation, telecommunications) from developed to developing economies. Furthermore, global sustainable development cannot be achieved without global climate governance and energy supply security. The United Nations (UN) has proposed Sustainable Development Goals (SDGs), which were adopted by 193 countries at the UN Sustainable Development Summit in September 2015. SDGs are representing an applicable framework to ensure global sustainable development. SDGs are stipulated on 17 goals with 169 targets; one of them is to take action toward climate change and the environment affected by energy efficiency use. The improper energy use caused severe environmental impacts (e.g., climate change, air pollution). One of the leading energy sources is the oil and gas (O&G) industry that forms a backbone for many global economies where it supplies more than 50% of global fuel consumption. Further, hydrocarbon energy sources are expected to keep its position as the superior source of energy in 2036 (BP, 2017).

The O&G industry has a massive impact on the environment regarding its importance to the other industries as fuel for electricity generation, heating, transportations, and intermediate commodities. Further, it is susceptible to external volatility, which determines the industry performance and structure. Various factors and issues affect the O&G industry trends, e.g., prices, environmental regulations, changes in demand patterns, and political instability. Recently in 2018, prices of crude oil have recovered after the overwhelming fall of the prices in 2008 and 2012. The prices recovery started when the member countries of the Organization of the Petroleum Exporting Countries (OPEC) and non-OPEC countries (Russia and Mexico) decided to cut down their amount of crude oil and natural gas production, as a quick response to the prices falling in 2014 through the convention that came into effect in 2016.

This action aimed to decrease the amount of crude oil supply to bush the prices up. Moreover, Libya and Nigeria had adhered to the agreement and participated in the cut oil production convention. The participation of those two countries led to form an unprecedented collaboration, accounting for around 50% of the global crude oil supply, which means the hydrocarbon price will increase then the investment will recover again. However, the OPEC and non-OPEC countries endeavored to diminish their throughput to control the crude oil price and maintain it above 60$/bbl. However, there is a converse trend that obstructs the cut down convention trend conducted by the US due to the high rate of unconventional shale oil production. Shale oil production totally changed the position of the US and its degree of dependency, in 2017 the US became a net exporter of crude oil, which influenced the international markets and led to drop in crude oil and gas prices. Besides, since 2015, unconventional shale production has participated by over 50% in the country's crude oil supply and 60% in the gas supply. According to the US Energy Information Agency (EIA), they will reach 53% and 70%, respectively, by 2020.

The US has become a dominant country and significant player in the global O&G industry, particularly in the light of shale unconventional oil boom. The US has the majority of O&G Companies headcounter, which gives the US a competitive advantage among the rest of the world. One of the US's primer advantages is that its refineries obtain the crude oil produced domestically, which reduces the total cost that affects the final prices. There are many crude oil producers (100 countries) around the globe[1]. The US is one of the leading producers in this industry in 2018. Figure 1.1 depicts the five crude oil-producing countries in the world between 1980-2018. The US is the top crude oil producer in 2018, followed by Russia, Saudi Arabia, Iraq, and Canada, respectively. The Top five producers participate by more than 50% of the total global crude oil production. Table 1.1 represents the share of the top 5 countries producers to the world in 2018. The highest participation is for the US by 13.2% of the total crude oil in the world, and the least contribution is for Canada by 5.2%.

[1] See: US Energy Information Administration (https://www.eia.gov/energyexplained/oil-and-petroleum-products/where-our-oil-comes-from.php).

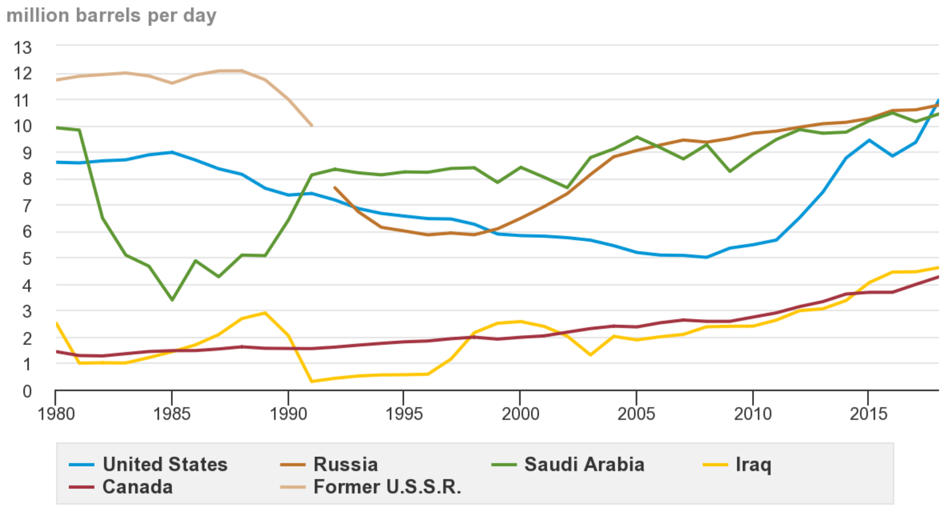

Figure1.1 Top Five Crude Oil Producing Countries, 1980-2018

Data source: https://www.eia.gov/energyexplained/oil-and-petroleum-products/where-our-oil-comes-from.php).

Table 1.1 Shares of Top Five Producers to the World in 2018

Country	*Percentage to the global crude oil production*
US	13.2%
Russia	13%
Saudi Arabia	12.6%
Iraq	5.6%
Canada	5.2%

Source: https://www.eia.gov/energyexplained/oil-and-petroleum-products/where-our-oil-comes-from.php).

The O&G is an unstable industry affected by factors such as prices, policies, cartels among countries, demand patterns, supply amounts, and overall investments. After the industry recovery in 2016 and 2018, many trends and issues have appeared, which one of the main issues is the O&G supply. The O&G supply is expected to be restricted due to problems affecting it, e.g., the unstable situation in Venezuela and Iran. This expected supply restriction is due to involuntary reductions and US sanctions on both countries. Furthermore, after Qatar's exit from the OPEC organization, that has weakened the OPEC power to some extent.

Another Promising trend is energy policies, which stipulate the rules and decisions from the US energy department and other international organizations. These policies aim to mitigate the environmental impact of the O&G industry and induce all the industry players to keep a balance between their O&G production and their environmental footprint. The O&G industry is the primary consumer of water and energy resources; therefore, it is subject to progressively stringent environmental norms. These environmental regulations force them to rethink all the industry procedures to preserve their license to operate. They also should provide guarantees and ensure transparency regarding their environmental management activities.

The O&G industry impacts the environment through all the industry stages from exploration and hydrocarbon production (E&P) to the crude oil refining process. The environmental effects are, notably, appeared on many various levels, e.g., air, water, soil, and, therefore, all living beings on the planet. Therefore, the most hazardous impact caused by the O&G industry is pollution, which is associated with all the industry activities from upstream to downstream segments. The contamination of the environment would be represented in solid waste, gas emission, wastewaters, aerosols generated through the E&P process, and refining (produce the major amount of pollution). Environmental pollution appears in many aspects, such as concentration greenhouse gases (GHGs), water contamination, and acid rain. All of these lead to loss of biodiversity as well as to the devastation of the ecosystem. Therefore, many non-governmental and intergovernmental organizations (NGOs and IGOs) globally frame the major efforts to uniform standards and operating practices for the O&G industry. For instance, the United Nations Environmental Program (UNEP), International Association of O&G Producers (IOGP), International Energy Agency (IEA), US Energy Information Administration (EIA), International Petroleum Industry Environmental Conservation Association (IPIECA), and International Maritime Organization (IMO). All of these Organizations endeavor to mitigate the impact of petroleum industry practices on the global environment through releasing initiatives, rules, frames, and goals, e.g., SDGs that enforce all the industry players to improve their performance regarding the environment.

The O&G market is unsteady and has undergone too many structural modifications as a response to environmental regulations, prices fluctuate, political situation, changes in demand patterns, and energy conservation. However, the market recently witnessed a recovery in the crude oil prices form 40$ in 2016 until 67$ in

2018[2]. According to the IEA, the global demand for fossil fuel is expected to rise by about 1/3 by the year 2035 (Olsson 2015). However, upstream capital expenditure is still restricted and has not been recovered, which means the companies still caution at least for the time being. As a result, the companies attempt to focus on showing returns rather than investing for new growth. All industry companies from upstream to downstream sectors work on analytics to improve their performance. However, not all O&G companies can operate their assets at their maximum capacity. In that case, O&G firms need to find innovative management approaches to stay competitive and maintain the fuel flowing.

1.2 The O&G Industry Structure

The O&G industry is sophisticated, and its activities are extended globally all over the regions. One of the main reasons that make the O&G industry complicated is the change in the governance structure of the world's oil supplies, where most of them are controlled by state agencies and not by private firms. The O&G industry structures and systems are generally defined according to their use in the O&G industry production stream. The stream range of the O&G industry includes explorations, extraction, transportations, refining crude oil, and processing natural gas into refined products used by the end-user consumer, which is used as a raw material for other industries. The O&G industry comprises three major segments: upstream, midstream, and downstream. In which, all industry companies along the value chain work together to provide and support a market operate efficiently. In the O&G industry, the value chain picks hydrocarbons generated at the wellhead (upstream) and conveys them (midstream) to end-users (downstream).

[2] US Energy Information Administration, "Short-term energy outlook," https://www.eia.gov/outlooks/steo/, accessed Sep. 9, 2019.

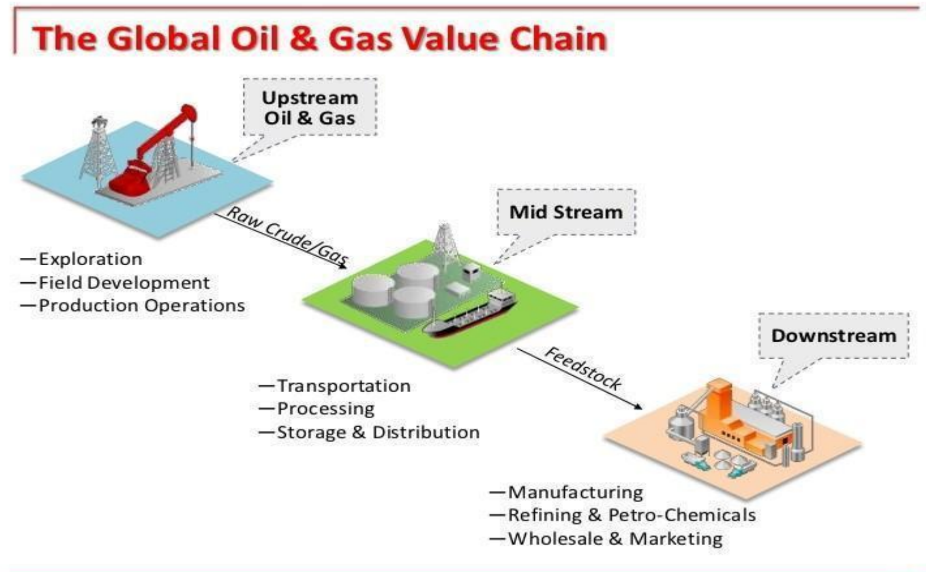

Figure 1.2 O&G Industry Structure

Source: https://energyroutes.eu/2016/05/23/porters-five-forces-model-for-oil-and-gas-industry

1.2.1 Upstream Segment

This segment is known as "Exploration and Production" sectors or E&P because it is related to activities that focus on searching for, recovering, developing, and producing crude oil and natural gas. The upstream sector is the most complex stage in the O&G industry, including drilling and heavy exploratory wells to extract the crude oil or natural gas. The upstream sector is all about wells, how in-depth and how far to drill them, where to locate them, and how to design, to operate, to construct, to exploit, and to manage them. In order to achieve the highest return on investment with the safest and lightest operational footprint, the wells could be complicated or straightforward according to the nature of drilling type (totally vertical or both deep and horizontal). Further, the E&P process is the primary stage in the O&G supply chain; at that stage, the reserves are converted to cash by maximizing the recovery of crude oil from subsurface reservoirs where the E&P process is efficiently extracting the hydrocarbons and treating them as needed to make them marketable. In the last decade, the unconventional upstream gets more attention in the O&G industry, it is defined as any resource extracted or produced by any technique other than the conventional vertical or slightly deviated well. The unconventional upstream has three main techniques, e.g., horizontal drilling, hydraulic fracturing, and subsea engineering (deep-water production). Horizontal drilling is not a recent technique, but the technology has quickly matured. This method reduces the volume of the drilling footprint and enables output along the length of the reservoir. Hydraulic fracturing (fracking) is the operation of injecting water, chemicals, and sand into wells. The resulting fractures in surrounding rock formations allow for the microscopic hydrocarbons to breakout. However, the public awareness of shale oil and fracking techniques, some of the most significant O&G discoveries in the last decade, have been found in the deep water off the coasts of Africa and South America, and the Gulf of Mexico as well. Subsea engineering innovations have made production economics from water depth exceeding 10000 feet.

1.2.2 Midstream Segment

Midstream is the middle or connected part of the O&G industry that provides the pivotal line between E&P areas and population centers where industrial refining and residential customers are located. It is generally defined as gas plants, Natural Gas Liquidation (NGL) generation and regasification, and O&G pipeline transport system (Devold 2013)3. This segment includes facilities and procedures that link between the upstream and downstream O&G segment. This segment's primer assets are field gathering, transmission pipelines, and processing plants where the midstream activities include gathering and processing, storage and linguistics, and transportation of crude oil and natural gas from the oil field to refineries. In this stage of the O&G industry, the transportation function is the main activity among all of the midstream activities, which includes trucking fleets, tanker ships, using pipelines, and rail cars.

1.2.3 Downstream Segment

This sector is the refining process of petroleum crude oil and the transformation and purification of raw natural gas. Further, it is the last stage in the O&G industry, which provides thousands of refined products made from crude oil to end-user customers. Refiners of petroleum crude oil and natural gas processors, who bring usable products to end-users and consumers, represent the downstream activities.

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3 Devold, H. 2013. Oil and gas production handbook An introduction to oil and gas production, transport, refining and petrochemical industry.Edition 3.0, Oslo.

The refineries also engage in the marketing and distribution of crude oil and natural gas products. Furthermore, the refined product includes customary products such as gasoline, jet fuel, heating oil, diesel, and asphalt for roads—besides, petrochemical products such as lubricants, synthetic rubbers, plastics, fertilizers, and pesticides. This segment has two distinct customers: wholesale customers, e.g., some manufacturing plants, power plants, shipping companies, airlines, etc., and retail consumers who use fuel products for heating and transportation.

1.3 Motivation

Despite many renewable and sustainable energy initiatives that aim to minimize the use of fossil fuel resources and reduce the environmental impacts of the O&G industry, we remain using O&G as a primary source of energy for decades. The O&G industry still plays an instrumental role in the current world energy system, which provides the whole world with more than half of its energy needs. Further, the O&G industry is the vital source for taxation and revenue for many countries (OPEC and non-OPEC); also, it offers the availability to convey the employment of technology from developed to developing countries. However, the O&G industry faces many challenges due to increasing global demand, prices volatile, and rigorous environmental regulations that seek to support the decarburization of the energy system. One of the main challenges that face the O&G companies is raising demands to state the implications of energy transitions for their operations and business models, and to clarify the efforts they can do to reduce GHG emissions. Otherwise, the companies along with all industry segments could not continue in the O&G markets, particularly with the rise of customer awareness toward the environment and climate change issues. The O&G companies along the O&G supply chain need to absorb and deal with such environmental pressure by clarifying their role in the societies in which they operate.

1.4 Objectives

This study poses six research questions as follows:

a. How can O&G upstream companies improve their environmental performance to meet the restricted environmental regulations, and to what extent can the type of company affect its environmental performance
b. What are the main factors needed to improve the performance of the O&G upstream sector?
c. Is the efficiency of O&G refineries affected by the region?
d. What are the main factors needed to enhance the performance of the O&G downstream sector?
e. Which segment of the O&G Industry can effectively adapt and meet the environmental regulations?
f. What are the recommended policies that could be supportive for O&G companies' managers to improve their efficiency?

This thesis seeks to investigate the overall (environmental & operational) performance of the O&G industry supply chain by examining the E&P companies (upstream sector) and O&G refining companies (downstream sector). Further, this study offers recommended policies that lead to improve O&G companies' efficiency to meet the environmental regulations and global market requirements. To explore these issues, this study has done the following:

The main work consisting of this dissertation is two-fold. Firstly, the study has focused on upstream segment E&P by comparing between the two kinds of companies that work in the E&P sector, the two types are integrated companies that have a supply chain from upstream to downstream retails, and independent companies that work only in the upstream sector. The first part examined two types of unified efficiency measures—operational and environmental—for 34 US O&G companies between 2011-2015. Using a unique balanced panel dataset, the dataset includes 7 majors O&G companies (integrated companies) and 27 independent companies. To measure the unified efficiency this study applied the non- radial Data envelopment analysis (DEA) environmental models to the dataset. Further, The Kruskal-Wallis (KW) rank sum test is utilized to investigate whether the two types of unified efficiency measures vary over time and whether there are differences between integrated and independent O&G firms.

Secondly, this study has concentrated on the downstream segment, by investigating the O&G refineries efficiency performance among four global regions between 2008 and 2017; using a unique unbalanced dataset of 696 refineries globally. This study utilized a combination of DEA and DEA-Discriminant Analysis (DA) to estimate an efficiency-based ranking of the O&G refineries. A KW rank-sum test was applied to test whether the average adjusted efficiencies measures varied among the four regions and if they changed over time. Thereafter, a Wilcoxon rank-sum test was utilized to explore whether the average adjusted efficiency levels differed between any of the two regions over the 10 years.

1.5 Structure of Thesis

The proceeding chapters are structured as follows. Chapter 2 provides literature reviews of the O&G industry studies (upstream & downstream) not only DEA studies but also those using other methodologies and policy studies. Chapter 3 discusses O&G supply chain characteristics and related industry issues. Chapter 4 discusses the DEA models as methodology of this dissertation. Chapters 5&6 present the two empirical studies, in which Chapter 5 investigates vertical structure and efficiency assessment of the US O&G companies by using DEA environmental models, and Chapter 6 investigates O&G refineries' operational efficiency in four global regions using DEA-DA. Chapter 7 provides general discussion and conclusion of this thesis along with future work directions.

Chapter 2

Literature Review

2.1 Introduction

This Chapter discusses three domains of O&G industry literature, i.e., the O&G supply chain studies management (SCM), O&G studies regarding the environmental practice, and the DEA application regarding the O&G industry. Where, this dissertation evaluates the O&G SCM by examining the two main segments (upstream and downstream) of the O&G supply chain and how the SCM can affect the company performance. Further, the first main empirical study in chapter 5 was considering the environmental perspective as a critical issue to achieve sustainability and evaluated the unified (environmental and operational) efficiency for the upstream segment. The DEA models also are applied as a methodology to evaluate the efficiency performance for both segments. Therefore, these three ranges are mentioned to support the thesis' purpose and explain the importance of the O&G industry from different perspectives.

2.2 O&G Supply Chain Studies

The O&G industry is playing an essential role in the current energy system formation (Roupas *et al*., 2011; Skouloudis *et al*., 2011). Where, the resources availability, the production technology, the future demand patterns, and the alternatives energy resources developments determine the role of the future usage of O&G (Doukas *et al.*, 2011). Most of the current O&G studies are focused on operational, organizational and environmental issues related to the incorporation of the sustainability concept and supply chain management (SCM) and value chain. See, for instance, Sear (1993) was the first study to discuss SCM and logistics in the downstream supply chain. He developed a linear programming model that engaged crude oil purchasing, transportation to the warehouse, and customers by considering various costs at every stage. Escudero *et al*. (1999) developed a two-stage model for supply and distribution scheduling of a multi-operator multi-product petroleum supply chain. The developed model considers demand, supply cost, and selling prices. Ross (2000) developed a profit-maximizing supply network model in the downstream oil supply chain by emphasizing performance planning through resource allocation. Relvas *et al*. (2006) developed a mixed integer linear programming (MILP) approach to model the problem of oil derivations pipeline transportation scheduling and supply management. The proposed approach covered inventory management and pipeline scheduling at distribution centers. Chima (2007) examined the role of supply chain management in the O&G industry and discussed the application of the Uniform Commercial Code (UCC) to supply chain management issues. Fernandes *et al.* (2013) suggested a profit-maximizing MILP model for strategic planning of downstream petroleum supply chain. The proposed approach solves the design of uni-entity and multi-entity networks consider transport modes, warehouse locations, and resource capacities and affectations of the network. Agarwal *et al*. (2016) investigated the role of management techniques viz., JIT, Kanban, TOC, TQM, TPM and ABC analysis for the orderly flow of goods and effective inventory management in the upstream sector of the O&G industry. BRASOVEANU (2017) analyzed the top 5 oil supermajors in terms of earnings, investments, and financial & operational performance along the entire business value chain, for a period of 5 years.

Furthermore, a group of researchers have emphasized the importance of the supply chain to improve and sustain O&G industry performance. See, for example, Lakhal *et al.,* (2007) examined green supply chain parameters for a Canadian petroleum refinery company. HUSSAIN *et al*. (2006) discussed the supply chain challenges and opportunities in the petroleum industry and on exchange practices that have long been utilized by the petroleum industry's giants around the world. Yusuf *et al.* (2013) examined the concept of sustainability adoption and related benefits on O&G supply chains in the UK. Ahamd *et al*. (2016), Raut *et al*. (2017), Moradinasab *et al*. (2018), and Florescu *et al*. (2019) discussed the concept of the sustainable supply chain management (SSCM) practice and its role in the O&G industry.

2.3 O&G Studies Regarding to The Environment

As a response to the wide range of the environmental regulations and sustainability requirements, the environmental performance of O&G companies became a necessity to mitigate their impacts on the environment and achieve the sustainability goals that required surviving in light of these restricted regulations. Therefore, a group of studies assessed the environmental performance for O&G companies. For instance, Jung *et al*. (2001) addressed a measurement of corporate environmental performance to combine environmental performance along five dimensions for petroleum companies. Inkpen and Ramaswamy (2012) attempted to explore the drivers that push state-owned O&G producers, the national oil companies to foster sustainability practices. The result revealed that sustainability practices are influenced by the proportion of independent directors, international exposure, and international involvement. Alazzani and Wan-Hussin (2013) evaluated the impact of Sustainability Reporting Guidelines issued in 2006 by the Global Reporting Initiative (GRI) on the environmental performance of eight O&G companies. Tesfay (2014) proposed how the Statoil Company coordinates with environmentally friendly cost efficient and effective sea transport outsourcing, strategy. Abdul- rahman *et al.* (2015) evaluated a research conducted on Egypt's first refinery flare gas recovery project, which could enhance sustainability and promote cleaner production within the Egyptian O&G industry. Shvarts *et al.* (2016) assessed the environmental responsibility rating of 19 Russian O&G companies based on their performance in 2014. The rating's results referred to a great variation in levels of environmental responsibility among the Russian O&G companies, with large and public companies focusing on gas receiving higher ratings than other small and private companies. George et al. (2016) investigate the barriers to, and enablers of, sustainability integration in the performance management systems of an O&G company. The results indicated that sustainability integration in performance management systems could lead to better management and control of sustainability performance in organizations.

Gonenc and Scholtens (2017) investigated the relationship between environmental and financial performance of fossil fuel firms. By examining a large international sample of firms in chemicals, oil, gas, and coal concerning several environmental indicators about financial performance over the period 2002–2013. The results indicated that environmental outperformance has no impact on financial performance for chemical firms, reduces returns and risks for coal companies, has a mixed effect on returns in O&G, and reduces financial risks for O&G firms. Financial outperformance reduces environmental performance in all fossil fuel (sub) industries investigated.

Ismail *et al.* (2018) examined the impact of determinants of corporate environmental disclosure quality on 116 O&G companies in 19 developing countries. They found that only 5 out of 12 hypothesized variables (company size, foreign ownership, profitability, leverage and membership of industry’s associations) are positively related to the CED quality. MOJARAD *et al*. (2018) investigated the significance of environmental policies through interviews with executives and stakeholders. The results found that the implementation of environmental protection policies is affected by the financial stability of the companies. Under difficult economic situations, companies seem less enthusiastic in strictly implementing those policies. Cardonui *et al.* (2019) investigated the quality of the Environmental, social, and governance (ESG) data for 41 O&G listed companies, focusing on their level of comparability. The results indicated that, despite the availability of a large amount of ESG data and the presence of sustainability frameworks, the comparability problem is still relevant.This at most depends on the absence of mandatory regulatory constraints in terms of social reporting. Orazalin and Mahmood (2018) explored the extent and nature of the sustainability reporting (SR) practices of the 54 largest O&G companies in Russia over the period 2012-2016, and investigated the impacts of the underlying factors on sustainability disclosures. The results referred to that standalone SR, firm age, and auditor type are the major factors in the dissemination of sustainability information in the Russian context. Further, SR that is released only in Russian provides more valuable sustainability information than SR that is published in both English and Russian. Frank *et al.* (2016) proposed an assessment framework that consolidates environmental sustainability indicators reported by 11 top global O&G companies into an integrative index to compare their performances. Furthermore, the proposed framework is based on a multi-criteria approach and scales transformation methods. Aung (2017) investigated Myanmar's Environmental impact system (EIA) quality. Further, evaluated the rate of EIA disclosure in the O&G segment and whether EIA in Myanmar is significant in mitigating the environmental impact of O&G operations on the environment. The results indicated that the level of disclosure and the quality of EIA reports in the O&G segment is higher than that of other sectors in Myanmar. Dongxiao and Tingyun (2015) examined environmental impacts related to hydraulic fracturing in shale gas development, regarding four aspects, water consumption, water contamination, seismic inducement and air pollution. Elhuni and Ahmad (2017) proposed a group of Key Performance Indicators (KPIs), to evaluate the sustainable production for the O&G segment based on the triple bottom line of sustainability. Schneider *et al.* (2013) analyzed the environmental and health and safety (EHS) performance for ten global O&G companies. The results showed that there are differences that exist in the O&G sector, which related to environment, health, safety, and sustainability. Meng (2017) evaluated the overall impacts of fracking on the environment and then designed a total environmental study paradigm that expertly examines the complicated relationship among the whole ecosystem. Chowdhury *et al*. (2018) measured the company-specific level of corporate social responsibility (CSR) activities from the provided information in the annual financial reports of O&G companies and determined the effects of CSR dimensions on firm value, to define whether the social, environmental, and economic dimensions of CSR are equally value-additive to O&G companies. Shvarts *et al*. (2018) discussed the evolution and current state of transparency of environmental performance data of 21 companies in the O&G sector in Russia from 2014 to 2016. Hove *et al*. (2002) investigated the various climate change strategies chosen by three major IOCs: ExxonMobil, TotalFinaElf, and BP Amoco. Pendley (2017) examined the environmental performance of O&G companies' upstream operations, which uses fracking technologies in the State of Pennsylvania. The results indicated that the smaller companies that specialize in E&P performed better on average than the majors IOC. Zhu and Zhu (2019) studied the impact of external energy policy and market environment changes and the internal effect of internal control and management on the economic benefits of petrochemical enterprises in China over the period (2011-2015). They found that changes in the energy policy have played a guiding, regulating, and promoting role in the development of petrochemical firms. While the more restrictions the market environment imposes on petrochemical firms. On the other hand, the fewer economic benefits the petrochemical enterprises receive.

2.4 DEA Studies Applied to O&G Industry

Many previous studies have used the DEA as a holistic tool to assess operational and environmental performance of private and public companies or decision-making units (DMUs). Zhou et al. (2008) provided a summary of 100 DEA publications in energy and environmental studies. Glover and Sueyoshi (2009) discussed DEA theories, models, and algorithms from the contributions of William W. Cooper, who is the father of DEA, dating back to the development of the L1 regression in the 18th century. They discussed popular DEA models and definitions of inputs and outputs used for the efficiency assessment. Sueyoshi et al. (2017) surveyed and classified approximately 700 DEA papers into several groups depending on the types of energy, energy efficiency, and environment or sustainability. Mardani *et al*.

(2018) summarized 145 DEA studies on energy and environmental issues. They provided an overview of studies using different DEA application types along with an explanation of their inputs and outputs. Furthermore, there is a group of studies that applies DEA in combination with the productivity index. See, for example, Färe *et al*. (2004) evaluated environmental performance using a formal index number (a kind of environmental productivity index), Wei et al. (2011) for a cross-country energy efficiency comparison, Hsu (2013) for an international comparison of efficiency in government health expenditures, Chan Oh and Hildreth (2014) measured technical improvements of energy efficiency in the automotive industry, Chowdhury *et al*. (2014) investigated productivity, efficiency, and technological changes with and without case-mix used as output categories in Ontario hospitals between 2002 and 2006, Shaoa et al. (2016) for an assessment of 30 sub-sub-sectors of China's nonferrous metal industry, Yang and Li (2017) conducted efficiency evaluations and policy analysis of industrial wastewater control in China, Wang and Li (2018) for an examination of the carbon emissions performance of 31 independent oil and natural gas producers in the US, . Feng *et al*. (2018) analyzed the sources of green total-factor productivity (GTFP) changes and its inefficiency of China's metal industry (MI) from 2000 to 2015, from regional and provincial view. Song *et al*. (2018) proposed a comprehensive decomposition framework that integrated production-theoretical decomposition analysis with index decomposition analysis to distinguish the driving factors of CO_2 emissions from China's iron and steel industry between 2000 and 2014. Further, they analyzed the different characteristics and drivers of CO_2 emissions at the national, regional and provincial levels. Feng *et al*. (2019) examined the sustainability of China's MI since the 21st century through an overview and an analysis of GTFP to elucidate the current situation of the energy and environment in the MI Sector from 2000 to 2015, Ma *et al*. (2019) examined the impact of government regulation on energy and CO_2 emissions performance in China's mining industry.

Acknowledging these previous studies on DEA applications, we need to point out that the number of DEA applications to the O&G industry is not widespread, even though the economic impact of the industry is huge. Thus, this section summarizes previous DEA studies applied to the efficiency analysis of O&G industry for investigating their efficiencies as follows:

Barros and Managi (2009) utilized a combination of DEA and Malmquist productivity index to analyze the change in productivity in nine oil blocks in Angola due to change in oil policy between 2002 and 2007. The results showed that the Angola oil policy towards technological change in blocks was the main factor responsible for increasing the productivity, since efficiency scores keep relatively constant. In addition, the traditional growth accounting method (e.g., Hicks neutral technological change) is not suitable for examining changes in productivity for Angola oil blocks. Francisco et al. (2012) used DEA models to examine environmental efficiency based on an undesirable output associated with production processes. They found that results obtained without using undesirable output as a basis could be misleading and that environmental regulations seemed to be less effective for efficient refineries. Ismail *et al*. (2013) analyzed the technical and technical efficiency (TE) to investigate the environmental performance and economic efficiency for 17 large O&G companies. Further, they applied Pearson's coefficient of correlation and the Spearman rank correlation coefficient Performance to examine eco-efficiency scores and economic scores. The Results indicated that there was a weak positive relationship between eco-efficiency and technical efficiency. Moreover, there was a weak correlation between revenue and eco-efficiency. Azadeh and Salehi (2014) introduced a new framework called integrated resilience engineering (IRE) as a developed version of a previous resilience-engineering (RE) concept. Then they measured the efficiency levels between managers and operators under RE and IRE frameworks by using DEA. The results indicated that, IRE framework is more efficient than RE and the gap between managers and operators under IRE has been improved by 88% compared to RE. Saxena *et al.* (2016) evaluated the efficiencies of the O&G and Power (OGP) in India. Using a dataset of 24 companies that are related to CNX Energy Index and CNX 500 Index of the National Stock Exchange. Using DEA to rank the companies according to their efficiency levels by calculating their technical, pure technical and scale efficiencies (SE). The results revealed that only 9 companies are efficient and the other units are inefficient. Further, some of the public sectors companies are inefficient due to using more inputs compared to the other companies in the same group for achieving the same level of efficiency. Vikas and Bansal (2019) evaluated pure TE and scale efficiency levels of 22 Indian O&G corporations from 2013 to 2017, and provided benchmark targets to the inefficient companies to achieve higher efficiency levels. The results revealed that 13 of all companies are efficient in terms of TE, 16 are pure technically efficient, and 14 in terms of SE. Further, the ineffective companies have to improve the utilized combination of inputs and outputs to achieve the targeted efficiency levels. Wegener and Amin (2019) developed a new inverse DEA model for optimizing GHG emissions through an application in the O&G industry in Canada and the US. The results revealed that roughly 57% of the samples DMUs are inefficient. Further, vast room exists within the current efficiency frontier to lower GHG emissions in the O&G sector.

Further, there are groups of studies applied other mathematical optimization models in the O&G Industry. See, for instance, Duffuaa *et al*. (1992) developed a linear programming (LP) model for oil production, gas processing and distribution for Saudi Arabia (KSA) to evaluate the impact of oil production on gas supply to associated vital industries in KSA. Further, clarify the minimum level of oil production to sustain its industries. Sear (1993) proposed a mathematical LP model for strategic logistics chain planning in the downstream oil industry, the study described the types of bulk transportation utilized, the major product classes, and indicated the risks related to changes to the logistics infrastructure. Iakovou (2001) presented an interactive multi-objective model for the logistic planning of maritime transportation of petroleum products. The proposed model optimized the transportation cost and risk, which help government agencies to form and set regulations to drive desirable routing schemes. Li *et al.* (2004) proposed a novel non-linear programming model for the planning of a refinery under uncertainty. The proposed model used to calculate the expectation of refinery revenue. Neiro and pinto (2004) proposed a mixed integer nonlinear programming model for the operation planning of petroleum supply chains from the oil fields infrastructure to the distribution terminals. The formulated model determines the optimal production, the transported through pipelines, the refinery operational variables, and the inventory levels of each entity. Persson and Göthe-Lundgren (2005) suggested an optimization model for the planning of shipping processes between refineries and depots, besides tanker routes and delivery quantities to depots. A column generation method along with valid inequalities, and constraint branching was utilized to fix the obtained model. Cao *et al*. (2009) proposed chance constrained programming models for refinery short-term crude oil scheduling problems under the assumption of stochastic demands. Fernandes *et al.* (2013) developed a new mixed integer linear program (MILP) for strategic design and planning of the downstream petroleum supply chain network. The model determines optimal depot locations, capacities, transportation modes, routes and network mannerism for long term planning. Ghaithan *et al.* (2017) developed a multi-objective optimization model for a downstream oil and gas supply chain. The model considers practical constraints such as mass balance, demand, capacities, service levels, and OPEC quota. Liao *et al*. (2018) developed an integrated optimization of the pipeline scheduling and pump scheduling through a discrete-time MILP model, for a single-source multi-product pipeline in pressure control mode, minimizing the pump cost, and the labor cost of pump stoppage/restart. Quinteros *et al.* (2019) presented an approach developed for the Empresa Nacional del Petroleo oil company in Chile to rationalize the distribution of some oil products through the main pipeline. The result indicated that the proposed model saved 10% in the cost of operating the pipeline and also allows a better quality of service. Moradinasab *et al.* (2018) investigated the petroleum supply chain with regards to sustainability for the first time using a game-theoretic approach. The results revealed that the overall profit of the petroleum supply chain in Nash equilibrium is 9.8% more than that in the Stackelberg equilibrium.

2.5 Thesis Contribution to The literature

Regarding the literature reviews, few studies consider the environmental perspective under the two disposability concepts (natural and managerial) when assessing the O&G companies' performance. The disposability concept is considered an early application of DEA environmental assessment; thus, a few studies considered this concept. Further, a few of the previous studies have taken a holistic view of the O&G supply chain from the exploration field to the distribution center. Therefore, this thesis is conducted to fill the gap in previous researches regarding these issues. Moreover, the examination periods and the methodology's combination are different from the literature survey in both empirical studies. Chapter 5 developed the study of Sueyoshi and Wang (2014) by using different time frames and datasets; also, Chapter 5 extended the DEA environmental models by the combined use of the Kruskal-wills rank-sum test for statistical examinations. Moreover, chapter 6 is the first study that applied a combination of DEA and DEA-DA to the O&G refineries. Besides, this chapter examines more firms than have been examined in previous studies; the larger dataset allows a broader analysis.

Chapter 3

O&G Supply Chain Characteristics and Industry Issues

3.1 Introduction

O&G supply chains are global firms, engaged in managing and organized activities across the O&G industry from crude oil production to refineries and petrochemical operations up to final product markets and end-users, passing through all necessary logistics inclusive transportation, storages, and distributions. Regarding today's global marketplace dynamic, the O&G supply chain companies have to optimize every aspect of their operations– supply, manufacturing, and distribution, to remain competitive (Grossmann, 2005). The main objective of O&G supply chain optimization is to utilize all production processes and sources to minimize the overall production, operations, transportation, storage, and distribution costs and satisfying customer demands as well. This chapter discusses the Characteristics of the O&G supply chain and related industry issues.

3.2 O&G Supply Chain Characteristics

The supply chain is characterized as an integrated process in which several distinct business units such as customers, suppliers, manufacturers, distributors, and retailers collaborate to obtain raw materials, process these raw materials into the required final products, and deliver these products to retailers/customers (Lambert and Cooper 2000). The O&G industry can be characterized as an ideal supply chain, which is defined as a compound structure of supply facilities linked together to serve end-user customers (Shen 2007). The O&G supply chain includes multiple units performing multiple functions classified according to their location in the O&G supply chain. Each segment has a business feature. These features differ according to the segment functions, circumstances of environmental work, key players, and regulations.

3.2.1 Business Characteristics of The Upstream Segment

The Upstream segment has key business characteristics regarding its work nature and extraction of curd oil process. These characteristics are high risk- high return, highly regulated, impacted by global politics, and intensive technology. Whereas, the upstream segment is arguably the most complex of all O&G business sectors, where there are various risks and unknowns in the exploration process, often hundreds of millions of dollars, and many years are spent before the O&G field becomes productive, mainly, offshore. The E&P segment is also regulated in terms of production access to reserves, pricing and taxation, and highly restricted environmental regulations. Moreover, this sector is a global business between producing nations and major oil companies that can be very complicated. Finally, in the last decade with developments of unconventional prospects, E&P has required extreme technology, and thus capital intensive.

3.2.1.1 Upstream Segment Main Players

The upstream segment has the main key players who operate the E&P processes. These key players include (a) Majors oil companies, which are known as integrated oil companies (IOCs) that work in all O&G industry sectors along with supply chains from upstream to downstream. These companies work all over the world, for example (Exxon Mobil, Shell, Total, BP, Chevron, ... etc.); (b) National oil companies (NOCs), which owned and managed by their governments. The NOCs produce more than 70% of global oil production and control 90% of oil preserves; these NOCs companies include ADNOC in UAE, Saudi Aramco in Saudi Arabia, PEMEX in Mexico, China National Offshore Oil Corporation (CNOOC), and many others; (c) Independent companies that work in all sectors not only the upstream segment and focus only in one sector in the O&G industry. In the upstream segment, those companies are known as E&P companies that work and concentrate only on exploring and producing crude oil, for example, Anadarko, Apache, ConocoPhillips, …etc; (d) Oilfield services companies that provide the technical and specialized equipment or services that are needed for drilling, exploring, extracting chemical supply, testing, improving, and maintaining crude oil and natural gas. It is worth mentioning that those companies do not mainly produce O&G or own any reserves. Further, the top ten oilfield services are Schlumberger, Halliburton, Baker Hughes, a GE company, Weir Oil & Gas, Emerson, Schneider Electric, National Oil well Varco, ABB, Siemens, and Weatherford Oil & Gas.

3.2.2 Business Characteristics of The Midstream Sector

The midstream sector has four major characteristics attributed to its role in the O&G supply chain, which are low-risk business, highly regulated, depends on the health of both upstream and downstream segments, and market prices affect demand. Those four characteristics identify the business frame of the midstream segment, where the business of transport O&G around, is considered a low capital investment, and thus low capital risk. In the past, the midstream functions in most of the O&G integrated companies were considered a tiny part of upstream and downstream operations. It is also highly regulated, particularly with regard to the use of fossil fuels, in which the midstream industry depends on fossil fuels to transport O&G. Thereby; it is sensitive to change in fuel costs and restricted air emission regulation[4].

Further, the midstream segment is located in between upstream and downstream segments, which depends on both an abundance of upstream supply and strong consumer demand because without a steady supply, there is no produced O&G to transport and store. Furthermore, without robust demand from downstream segment consumers, the midstream segment could not do its function, as well. Besides the impact of upstream and downstream sectors, there are other external factors affecting the midstream segment, e.g., oil prices, refineries margins, quality of natural gas, and petrochemical industry markets.

3.2.2.1 Midstream Segment Key Players

There are various types of firms operating in the midstream sector, e.g., integrated O&G companies, independent midstream companies, and sponsored midstream companies. However, The midstream industry is more concentrated in the US and Canada than in the rest of the world. This concentration is attributed to the sizable privately owned oil pipelines and storage facilities in the US and Canada. The designation in the US of crude oil transportation and storage as a detached part of the supply chain is what permits the midstream industry to exist.

According to the significant growth in Master Limited Partnership (MLP) structure in the US, the midstream sector becomes familiar to companies outside the O&G industry. The MLPs have different midstream activities; some of them focus

[4] See https://www.sasb.org/wp-content/uploads/2019/08/NR0102_OG_Midstream_2014_06_24_Industry_Brief.pdf

only on transmission pipeline, some on oil, many on natural gas, and the rest on NGL process through converting natural gas to high valued NGLs or petrochemical feedstock. Further, the energy MLP structure is solely a US business entity. Thus, Midstream key players include; for example, MarkWest Energy Partners, Boardwalk Pipeline Partners, Magellan Midstream, Kinder Morgan, Williams Companies, Trans Canada, Targa Midstream Services, Sunoco Logistics, Plains All American, Oneok Partners, Energy Midstream, Genesis Energy, Gibson Energy, Aux Sable, Bridger Group, DCP Midstream, Enbridge Energy Partners, and Enterprise Products Partners.

3.2.2.2 Major Midstream Operating Components

Gathering: Field gathering is the initial step of the midstream process, where O&G production comes from hundreds of wells through a "spider web" of small-diameter pipelines to a central location, the oil is moved. Unlike a crude oil natural gas is different; it cannot store near the well. It runs through a series of smaller diameter pipelines to a central treating to remove water and impurities and separate out the NGLs.

Fractionation Processing: The fractionation is the process that is needed to separate the high-valued NGLs from natural gas production. While processing is the stage required for installation of surface units are required to measuring oil, gas, and water production rate from the reservoir, O&G separation from the wastewater, excluding any impurities, and O&G are temporarily stored until they are ready to be moved.

Transportation: This is the stage that crude oil and natural gas are delivered through transportation, pipeline transmission. The O&G are transported to processing facilities, and from there to end-users, by pipeline, tanker/barge, truck, and rail. Pipes are the most economical transportation method and are most suited to movement across longer distances, e.g., across continents. In particular, the US has hundreds of thousands of crude oil, miles of natural gas and liquids pipelines. Currently, in the US, rail becomes an essential transportation method, while most US shale plays do not access existing pipelines because of the lack of infrastructure in shale oil plays.

Storage: Storage for crude oil and refined products is a simple method compared to natural gas. The crude oil generally is stored in field tank batteries, refinery tanks, and holding tanks. On the other hand, natural gas is stored underground until it is ready to be transported to the market. The typical storage facilities for natural gas are depleted gas reservoirs, salt caverns, and aquifers.

3.2.3 Business Characteristics of the Downstream Segment

This segment has four major characteristics based upon the role of the downstream sector in O&G supply chain, which focuses on refining process and marketing issues. These characteristics include (a) Margin business, which is defined as the difference between the final price of the refined products and the cost of the crude oil as a raw material. The margin is sensitive to crude oil prices; hence, there is a negative relationship between them; (b) Complex segment because it is a very sophisticated segment that includes various activities such as refining, petrochemicals, distribution, and wholesale and retail marketing; (c) Required a global perspective, which is imperative to consider the global perspective of the nature of the energy supply chain. Further, the impact of market powers on both feedstock and product prices; (d) Deals with end-users because this segment links between refineries, petrochemical companies, and the final consumers.

3.2.3.1 Downstream Participants

The participants of this segment are oil refining, petroleum product distributors, petrochemical plants, natural gas distributors, retail outlets and marketing divisions of the major integrated oil companies such as BP, Exxon, Chevron, Shell, and Total. In addition, the major US independent refineries such as Valero, Tesoro, Phillips 66, Sunoco, and Murphy. Besides, the NOCs such as Aramco and ADNOC are rapidly investing in refining and petrochemical industries both at home and abroad, as a step for facing oil price volatility, meeting the increase of domestic demand, and securing their market share in light of booming supply from unconventional resources.

3.3 Major Challenges of O&G Industry

The O&G industry has lots of influences in the world today. The O&G industry has a direct impact on every other commodity in the market. Thus it is crucial to determine challenges and solutions by technological innovation to maintain global economic balance and need. Further, The O&G companies operate within competitive and interval national and global frameworks. However, new geographies expansion is opening up new avenues for revenue growth for O&G companies, and it is also simultaneously raising the complexity and risk of business operations. Therefore it is important to shed the light on major O&G industry challenges as follows:

3.3.1 Minimizing total cost to stay competitive:

One of the main O&G industry challenges is producing crude oil and refined products at a low price to remain competitive on the O&G market. Therefore, maximizing the production process and environmental utility performance is vital for the O&G industry. However, in light of the instability of the oil prices and restricted environmental regulations that argue to decarbonize the O&G industry outcomes, it becomes tough to keep the total cost at the minimum level.

3.3.2 Enhancing performance to secure the assets valorization:

O&G companies have to sustain the supply of their O&G sources and search for a new field or source to maintain their needs from crude oil that is used in the production process. So that the O&G companies have to increase their productivity, preserve their industrial assets and avoid unplanned shutdowns.

3.3.3 Improving the environmental performance to meet market highly standard regulations:

The O&G industry is a primer consumer of energy and water resources, and therefore it is undergoing strict environmental regulations. This regulation forced them to consider the environmental perspective in their operating process to avoid withdrawal for their operating license. Furthermore, they have to ensure transparency in their environmental management performance reports that cover their activities. Otherwise, they could be encountering losing their market share.

3.3.4 Moving towards alternatives and renewable energy sources:

Using alternatives such as Electric vehicles (EVs) is obtaining strength, particularly in China, where the government has a stringent policy towards pollution recession, a de-emphasis on coal, and more significant sanctions against polluters. Further, renewable resources become a global orientation as a clean solution instead of fossil fuel resources.

3.3.5 Building an effective collaboration with oilfield services to enhance logistics:

It becomes an essential step for O&G companies to collaborate with oil field services companies to secure their third party suppliers. Where for O&G companies, oilfield services perform business-critical functions. Even the giant integrated O&G companies, e.g., Shell, ExxonMobil, and Chevron, must rely on those third party companies to provide expertise and specialist equipment for different parts of the O&G supply chain. Where after BP’s Deepwater Horizon rig disaster, these issues became part of public consciousness.

3.3.6 Utilize metrics as a “vital sign” of the efficiency of the operational improvement efforts:

Utilizing appropriate measurement tools is crucial to predict and help the staff to respond to issues before they become problems, thus enhancing the overall companies’ efficiency. For example, the next generation of asset management tool, known as Advanced Condition Monitoring (ACM), supplies a new set of predictive capabilities by observing real-time information on equipment and operations, then using analytics to detect trouble before it happens. Whereas, ACM decreases the time to uncover defects in equipment through real-time warning management based upon sensing abnormalities, and minimize the time to solve issues through automated and collaborative data sharing across the extended venture.

Over the above, there are other challenges represented as a set of practical factors that have hit major O&G producing companies in the process of achieving sustainable development policies. These challenges are the fluctuation of Crude oil prices (Regnier, 2007); increasing of shareholders pressure on managers to focus on value creation instead of output due to low returns on investments (Ramos, Taamouti, Veiga, & Wang, 2017); the complexity of the E&P segment such as the drilling and production process (Gupta & Grossmann, 2017); health Safety and Environment (HSE) compliance still critical - especially in the recent environment of volatile prices and cost savings (Neill, 2017); considering corporate social responsibilities (CRS) (Banerjee, 2017) and Protection of the social permission of operation (Tomlinson, 2017); R&D and innovation in light of fluctuation of fiscal regimes (Hall & Vredenburg, 2003); and dealing with the expanding size of data and knowledge management (Bratianu & Bolisani, 2015); and The unsettled partnership of NOC-IOC (Whitson, 2009).

Chapter 4

Data Envelopment Analysis

4.1 Value of DEA for Analyzing Utility Industry

DEA is a nonparametric methodology, assuming no random mistake, utilized to estimate production frontiers; this method is commonly used in operations research and economics (Sickles & Zelenyuk 2019). DEA is a holistic methodology based on a linear programming approach for assessing the efficiency performance of multiple decision-making units[5] (DMUs) when the production process shows a structure of multiple inputs and outputs (Yishi et al. 2014). Practitioners and researchers who study productivity issues utilize DEA as a benchmarking tool mainly for measuring efficiency and performance analysis. Further, the DEA estimates the "relative" efficiency of a selected entity in a specific group of units and criteria.

Recently, DEA has become one of the most common fields in operations research, with implementation covering a wide range of context (Thanassoulis, 2001). In the benchmarking process the efficient DMUs may not necessarily form a "production frontier" but rather lead to a "best-practice frontier" (Charnes A., W. W. Cooper and E. Rhodes (1978)). DEA models infer the weights of input and output through an optimizing computation. Thus, DMUs can be categorized into efficient and inefficient. In inefficient DMUs, they inform the target values of inputs and outputs, which would lead to efficiency. For more extensions with accompanying cases of utilizations of conventional DEA, see (Banker et al. (1984), Banker et al. (1989), Charnes and Cooper (1985) and Seiford and Thrall (1990)). Compared to other parametric methods, e.g., stochastic frontier analysis (SFA), DEA's significant advantages are its ability to deal with DMUs of multiple inputs and multiple outputs, and the nonparametric treatment of data without assuming any functional form, e.g., production function, for the relationship between inputs and outputs. The DEA model, in its conventional form, can only address desirable outputs, e.g., production quantity and profit. Due to the predominance of undesirable outputs, in reality, DEA environmental assessment models have proposed to deal with both types of outputs, Mo and Wang (2019).

The DEA is firstly created for practical needs. However, the regulators realized the usefulness of DEA in regulations benchmarking (Bogetoft and Nielsen 2003). For example, in 1991 the Norwegian Energy regulator (NVE)[6] has released a

[5] DMU is a technical word of in DEA community and It could be defined in different ways (banks, segments, companies, hospitals, etc)

[6] See: https://www.nve.no

different regulatory regime, which has mainly used DEA for its benchmarking analysis for its electricity distribution sector to determine the cost-efficient production level. In particular, yardstick competition regime (first regulatory regimes that used DEA), which aims to set an individual cost target for each distributor that equals the realized cost by other (comparable) agents. The DEA application has a positive impact on the yardstick regulation, in which a change in the production profile can be easily considered. Further, in Norway, incentive regulation with a price cap was presented in 1997 for electricity distribution system operators; it is revised every five years. Individual efficiency scores were obtained from a DEA benchmarking, with dimensions of output being network length, the number of transformers, energy supplied, and the number of customers. Furthermore, in 1994 the Water Services Regulation Authority (OFWAT)[7], which is the body responsible for economic regulation of the privatized water and sewerage industry in England and Wales, utilized a DEA and OLS regression to estimate the potential efficiency saving at water companies by improved operating efficiency. The DEA and OLS results offered a ranking of companies based on their efficiencies. Based on those ranks, the OFWAT considered further factors, e.g., quality of customer service provided by every company and the strategic plane before reaching the final price determination it set.

4.2 Relative Efficiency Measurement

While DEA is a managerial tool for measuring the relative efficiency of chosen homogeneous DMUs. It is important to mention the structure of the relative efficiency model, which is addressed by Farrell (1957). The model is assessing weights to the variables (inputs & outputs) therefore the relative efficiency score is calculated as a ratio of the weighted sum of the outputs to the weighted sum of the inputs as follows:

$$\text{Efficiency} = \frac{Weighted\ sum\ of\ outputs}{Weighted\ sum\ of\ inputs} \qquad (4.1)$$

Here the efficiency measurement process represented by the model (4.1) considered the existence of various inputs and outputs. Here, it is popular to utilize the same set of weights to the inputs or outputs of all DMUs. In this way, all DMUs are received with equal importance to a particular input or output. Consider n DMUs with m

[7] See: https://www.ofwat.gov.uk/regulated-companies/ofwat-industry-overview/

inputs and s outputs. Let x_{ij} be the inputs and y_{rj} be the outputs of DMU_j. The mathematical exemplification of the model (4.1) would be as follows:

$$Q_j = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \quad j= 1,2,..,n. \qquad (4.2)$$

Where,

Q_j is the efficiency ratio of j *th* DMU

u_r, *r*=1,….,*s* are weights assigned to *r-th* output

v_i, *i*= 1,…..,*m* are weights assigned to *i-th* intput

y_{rj} is the quantity of output *r for j th* DMU

x_{ij} is the quantity of input *i for j th* DMU

Here the utilized weights have cost-price implications. The inputs weights correspond to their costs while outputs weights to their prices. Further, the efficiency is ranging between 0 (the worst) and 1(the best). The decision-maker assigned a common set of weights to all DMUs. Therefore, the DMUs are not given the freedom to select their own set of weights for their inputs and outputs. Consequently, the DMUs' efficiencies are determined under this predefined set. Thus, this model has no possibility of increasing the efficiency score of a DMU using the way of assigning the weights that are most appropriate for that DMU.

4.3 Additive Model

Additive model was developed by Charnes *et al*[8]. (1985). This model combines both orientations (input, output) in a single model, which deals with the input surpluses and output shortfalls directly, i.e. additive model is considered as an alternative to the two radial models. Further, it can distinguish efficient and inefficient DMUs using the existence of slacks[9]. Also, The additive model has no scalar measure (ratio efficiency). The mathematical structure for additive model is as follows:

[8] See appendix B for DEA conventional models that proposed by Charnes *et al*. and Banker *et al*.

[9] There are many efforts to determine inefficiency based upon the slacks. See, Russell (1985,1988), Pastor (1996), Lovell and Pastor (1995), Torgersen et al. (1996), Cooper and Pastor (1997), Cooper and Tone (1997), (Thrall 1997), and many others have approached several formulae for finding a scalar measure.

$$
\begin{aligned}
&Max\ Z = \sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \\
&s.t.\ \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = x_{io} \quad i=1,..,m, \quad (4.3)\\
&\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{ro} \quad r=1,\dots,s,\\
&\sum_{j=1}^{n} \lambda_j = 1 \quad j=1,2,..,n,\\
&\lambda_j \geq 0, \quad s_i^-, s_r^+ \geq 0.
\end{aligned}
$$

Here the objective function represents the inefficiency level, and the level of efficiency would be calculated by subtracting the inefficiency level from the unity.

4.4 DEA Environmental Assessment Models

As an extension of DEA conventional models, DEA environmental assessment models can deal with not only desirable outputs but also undesirable outputs where the inputs produce both of which through the production process. These environmental models allow companies to evaluate all economic activities regarding both economic success and environmental protection. Thereby they are enhancing the corporate level of social sustainability. The DEA environmental models can be categorized into two groups[10]: radial models and non-radial models, Sueyoshi and Wang (2014). The radial models suppose proportionate contraction of inputs and proportionate expansion of outputs in seeking better production efficiency, whereas the non-radial models reject this assumption. An essential feature of the radial assessment is that it combines an inefficiency score to define the level of unified efficiency (UE) measures Where each of which is measured by subtracting the inefficiency score from unity, which determines the level of three unified efficiencies by the total amount of slacks. Moreover, the radial approach incorporates a minimal number (ε) that indicates the relationship between the inefficiency score and the overall amount of all slacks. The combination of such a tiny number can decrease the impact of slacks in the UE measurement, and it can control the magnitude. The unification of the DEA environmental models refers to a combination of the operational performance of desirable outputs and the environmental performance of undesirable outputs. See Sueyoshi and Goto (2012b) for output separation and unification.

[10] Radial models, or Farrell type efficiency models, directly incorporate an efficiency score in the objective function. On the other hand, non-radial models do not incorporate efficiency score in the objective function, because they measure the efficiency level by the slacks of the production factors

4.4.1 Disposability Concepts

In order to formulate the DEA environmental assessment models, the disposability concepts "natural disposability" and "managerial disposability" are needed to introduce. To explain both of which more clearly, suppose there are (n) DMUs, $X \in R_{+}^{m}$ as an input vector with m inputs, $G \in R_{+}^{s}$ as desirable output vector with s desirable outputs, $B \in R_{+}^{h}$ as undesirable output vectors with h undesirable outputs, and the subscript j is used to stand for the j-th DMU, whose vector components are positive. Then, Production technology under natural disposability$P^{n}(X)$ and managerial disposability $P^{m}(X)$ under CRS can be expressed by the following output vectors, respectively:

$$P^{n}(X) = \{(G,B): G \leq \sum_{j=1}^{n} G_j\lambda_j, B \geq \sum_{j=1}^{n} B_j\lambda_j, X \geq \sum_{j=1}^{n} X_j\lambda_j, \sum_{j=1}^{n} \lambda_j \geq 0, \lambda_j \geq 0 \ (j = 1, \dots, n)\}, \text{ and} \qquad (4.4)$$

$$P^{m}(X) = \{(G,B): G \leq \sum_{j=1}^{n} G_j\lambda_j, B \geq \sum_{j=1}^{n} B_j\lambda_j, X \leq \sum_{j=1}^{n} X_j\lambda_j, \sum_{j=1}^{n} \lambda_j \geq 0, \lambda_j \geq 0 \ (j = 1, \dots, n)\}$$

The differences between the two disposability concepts are their respective inequality constraints. For natural disposability, or $P^{R}(X)$, the input constraint is $X \geq \sum_{j=1}^{n} X_j\lambda_j$, while for managerial disposability, or $P^{G}(X)$, the constraint is $X \leq \sum_{j=1}^{n} X_j\lambda_j$. The unification of the two-production possibility sets results in the following output set, where ∪ stands for a union set.

$$P^{u}(X)=P^{R}(X) \cup P^{G}(X). \qquad (4.5)$$

By changing these axiomatic structures to VRS, the production and pollution possibility set becomes as follows:

$$P^{R}(X) = \{(G,B): G \leq \sum_{j=1}^{n} G_j\lambda_j, B \geq \sum_{j=1}^{n} B_j\lambda_j, X \geq \sum_{j=1}^{n} X_j\lambda_j, \sum_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0 \ (j = 1, \dots, n)\}, \text{ and} \qquad (4.6)$$

$$P^{G}(X) = \{(G,B): G \leq \sum_{j=1}^{n} G_j\lambda_j, B \geq \sum_{j=1}^{n} B_j\lambda_j, X \leq \sum_{j=1}^{n} X_j\lambda_j, \sum_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0 \ (j = 1, \dots, n)\}.$$

4.4.2 Unified Efficiency under Natural Disposability (UEN)– Non-Radial Model

In order to formulate the DEA non-radial model, the following three data ranges are used for the objective functions related to each production factor, inputs, desirable outputs, and undesirable outputs, respectively:

First let us assume there are n DMUs denoted by (j=1,..,n), each DMUs utilizes m inputs represented by (i= 1,…,m) to produce (r) desirable outputs labeled as (r=1,…,s) and f undesirable outputs represented by (f=1,…h). For the *j-th* DMU, let $x_{ij} \in R_{+,}\ g_{rj} \in R_{+}, and\ g_{rj} \in R_{+}$ refer to *i-th* inputs, *r-th* desirable outputs, and *f-th,* respectively. The following three sets of numbers represent the data adjusted ranges related to inputs, desirable outputs, and undesirable outputs, respectively:

$$
\begin{aligned}
R_i^x &= (m+s+h)^{-1}(\{x_{ij}|j=1,\dots n\} - \{x_{ij}|j=1,\dots,n\})^{-1} \text{ for } i = 1,\dots,m,\\
R_r^g &= (m+s+h)^{-1}(\{g_{rj}|j=1,\dots n\} - \{g_{rj}|j=1,\dots,n\})^{-1} \text{ for } r = 1,\dots,s, \quad (4.7)\\
R_f^b &= (m+s+h)^{-1}(\{b_{fj}|j=1,\dots n\} - \{b_{fj}|j=1,\dots,n\})^{-1} \text{ for } f = 1,\dots,h.
\end{aligned}
$$

A non-radial DEA model to measure the level of UEN of the k-th DMU with natural disposability is described as follows:

$$
\begin{aligned}
\text{Maximize } & \textstyle\sum_{i=1}^{m} R_i^x d_i^{x-} + \sum_{r=1}^{s} R_r^g d_r^g + \sum_{f=1}^{h} R_f^b d_f^b\\
\text{s.t. } & \textstyle\sum_{j=1}^{n} x_{ij}\lambda_j + d_i^{x-} = x_{ik} \quad (i=1,\dots,m), \quad (4.8)\\
& \textstyle\sum_{j=1}^{n} g_{rj}\lambda_j - d_r^g = g_{rk} \quad (r=1,\dots,s),\\
& \textstyle\sum_{j=1}^{n} b_{fj}\lambda_j + d_f^b = b_{fk} \quad (f=1,\dots,h),\\
& \textstyle\sum_{j=1}^{n} \lambda_j = 1,\\
& \lambda_j \geq 0\ (j=1,\dots,n),\ d_i^{x-} \geq 0\ (i=1,\dots,m),\\
& d_r^g \geq 0\ (r=1,\dots,s)\ \&\ d_f^b \geq 0\ (f=1,\dots,h).
\end{aligned}
$$

Where d_i^x is a slack variable related to the i-th input $(i=1,\dots,m)$; d_r^g is a slack variable related to the r-th desirable output $(r=1,\dots,s)$; d_f^b is a slack variable related to the f-th undesirable output $(f=1,\dots,h)$. The DEA model proposed here also needs a vector $\lambda = (\lambda_1, \ldots, \lambda_n)^T$ to express the unknown "intensity" or "structural" variables. Here, The model treats the input-related deviations $+d_i^x$ $(i = 1, \ldots, m)$ to attain the status of natural disposability where all inputs can be decreased to improve operational efficiency[11].

The UEN is obtained by subtracting the level of inefficiency from unity. The inefficiency in the objective function is expressed in parenthesis.

$$UEN = 1 - [\sum_{i=1}^{m} \quad R_i^x d_i^{x*} + \sum_{r=1}^{s} \quad R_r^g d_r^{g*} + \sum_{f=1}^{h} \quad R_f^b d_f^{b*}] \qquad (4.9)$$

Here, all slack variables with asterisks are specified at the optimality of Model (4.8).

Further, all slakes are calculated as follows:

$$d_i^{x-*} = x_{ik} - \sum_{j=1}^{n} \quad x_{ij}\lambda_j^*, d_r^{g*} = \sum_{j=1}^{n} \quad g_{rj}\lambda_j^* \; - g_{rk}, and \; d_f^{b*} = b_{fk} - \sum_{j=1}^{n} \quad b_{fj}\lambda_j^* \; (4.10)$$

Model (4.11) has a dual formulation as follows:

$$Min. \; \sum_{i=1}^{m} \quad v_i x_{ik} - \sum_{r=1}^{s} \quad u_r g_{rk} + \sum_{f=1}^{h} \quad w_f b_{fk} + \sigma \quad (4.11)$$

$$\begin{aligned} s.t. \quad & \sum_{i=1}^{m} \quad v_i x_{ij} - \sum_{r=1}^{s} \quad u_r g_{rj} + \sum_{f=1}^{h} \quad w_f b_{fj} + \sigma && (j=1,\ldots,n), \\ & v_i \geq R_i^x && (i=1,\ldots,m), \\ & u_r \geq R_r^g && (r=1,\ldots,s), \\ & w_f \geq R_f^b && (f=1,\ldots,h), \\ & \sigma: URS. \end{aligned}$$

Where v_i *(i=1,…, m),* u_r*(r=1,…,s),* and w_f *(f=1,…,h)* all of which are dual variables related to the 1st, 2nd, and 3rd groups of constraint in model (4.11). The dual variable σ is obtained from the 4th line in the model (4.11). An essential feature of this dual model is that all variables are positive, which means all the production functions are fully utilized in the suggested environmental assessment. Then, the unified efficiency is determined by the following mathematical formulation:

[11] See: (Sueyoshi, T., Goto, M. 2018.Environmental Assessment on Energy and Sustainability by Data Envelopment Analysis, First Edition, John Wiley & Sons Ltd.) For more explanation.

$$UEN_v^{NR} = 1 - [\sum_{i=1}^{m} v_i^* x_{ik} - \sum_{r=1}^{s} u_r^* g_{rk} + \sum_{f=1}^{h} w_f^* b_{fk} + \sigma^*]. \quad (4.12)$$

Where UEN_v^{NR} denoted to UEN for non-radial model under VRS.

4.4.3 Unified Efficiency under Managerial Disposability (UEM)

The following non-radial model measures the level of UEM of the k-th DMU. The only difference between Models (4.8) and (4.13) is the sign of the input slack variable (d_i^x) at the first constraint equation. The difference holds large implications

$$\begin{aligned}
\text{Maximize} \quad & \sum_{i=1}^{m} R_i^x d_i^{x+} + \sum_{r=1}^{s} R_r^g d_r^g + \sum_{f=1}^{h} R_f^b d_f^b \\
\text{s.t.} \quad & \sum_{j=1}^{n} x_{ij}\lambda_j - d_i^{x+} = x_{ik} \quad (i = 1, \dots, m), \\
& \sum_{j=1}^{n} g_{rj}\lambda_j - d_r^g = g_{rk} \quad (r = 1, \dots, s), \qquad (4.13) \\
& \sum_{j=1}^{n} b_{fj}\lambda_j + d_f^b = b_{fk} \quad (f = 1, \dots, h) \\
& \sum_{j=1}^{n} \lambda_j = 1, \\
& \lambda_j \geq 0 \ (j = 1, \dots, n),\ d_i^x \geq 0 \ (i = 1, \dots, m), \\
& d_r^g \geq 0 \ (r = 1, \dots, s) \ \&\ d_f^b \geq 0 \ (f = 1, \dots, h).
\end{aligned}$$

The model considers the input-related deviations $-d_i^{x+}$ $(i = 1, \dots, m)$ to obtain the status of managerial disposability where all inputs can be maximized to enhance the environmental performance of the k-th DMU while satisfying the requirements for the desirable and undesirable outputs. As with the UEN, the k-th DMU's degree of UEM is measured by subtracting the inefficiency, or the value of the equation in parenthesis, from unity.

$$UEM_V^{NR} = 1 - [\sum_{i=1}^{m} R_i^x d_i^{x*} + \sum_{r=1}^{s} R_r^g d_r^{g*} + \sum_{f=1}^{h} R_f^b d_f^{b*}] \qquad (4.14)$$

Model (4.13) has a formulation of dual model as follow:

$$\begin{aligned}
Min. \quad & -\sum_{i=1}^{m} v_i x_{ik} - \sum_{r=1}^{s} u_r g_{rk} + \sum_{f=1}^{h} w_f b_{fk} + \sigma \qquad (4.15) \\
s.t. \quad & \sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r g_{rj} + \sum_{f=1}^{h} w_f b_{fj} + \sigma \quad (j=1,\dots,n), \\
& v_i \geq R_i^x \qquad (i=1,\dots,m), \\
& u_r \geq R_r^g \qquad (r=1,\dots,s), \\
& w_f \geq R_f^b \qquad (f=1,\dots,h), \\
& \sigma: URS,
\end{aligned}$$

Where v_i *(i*=1,…, *m)*, u_r*(r*=1,…,*s)*, and w_f *(f*=1,…,*h)* all of which are dual variables related to the 1st, 2nd, and 3rd groups of constraint in model (4.13). The dual variable σ is obtained from the 4th line in the model (4.13).

The unified efficiency is determined by the following mathematical formulation:

$$UEM_v^{NR} = 1 - [-\sum_{i=1}^{m} v_i^* x_{ik} - \sum_{r=1}^{s} u_r^* g_{rk} + \sum_{f=1}^{h} w_f^* b_{fk} + \sigma^*]. \quad (4.16)$$

The previous equation refers that each dual variable determines a change in the degree of unified inefficiency under managerial disposability, this change occurs as a result of one unit increase in each production factor.

4.4.4 Unified Efficiency Under Natural Disposability (UEN) Radial Model

The radial model for DEA environmental assessment is the methodological alternative to the non-radial approach for DEA environmental assessment. The radial models suppose proportionate retraction of inputs and proportionate expansion of outputs in seeking superior production efficiency, while the non-radial models discard this assumption, Mo and Wang (2019). A remarkable feature of the radial approach is that it combines an inefficiency score to define the level of unified efficiency measures, each of which is measured by subtracting the inefficiency score from unity. The analytical characteristic is different from the non-radial measurement, which determines the level of unified efficiencies by the total amount of slacks. Moreover, the radial model incorporates a small number (ε) that denotes the relationship between the inefficiency score and the total amount of all slacks. Whereas the incorporation of (ε) can decrease the influence of slacks in the unified efficiency measurement and it can dominate the quantity of all dual variables to be positive so that all production factors are fully applied in the proposed approach.

As the previous non-radial DEA for environmental assessment modes, the following three adjusted data ranges are fixed and available before running the DEA models, since they are constructed based upon the sample.

$$R_i^x = (m+s+h)^{-1}(\{x_{ij}|j=1,\dots n\} - \{x_{ij}|j=1,\dots,n\})^{-1} \text{ for } i = 1,\dots,m,$$
$$R_r^g = (m+s+h)^{-1}(\{g_{rj}|j=1,\dots n\} - \{g_{rj}|j=1,\dots,n\})^{-1} \text{ for } r = 1,\dots,s, \quad (4.7)$$
$$R_f^b = (m+s+h)^{-1}(\{b_{fj}|j=1,\dots n\} - \{b_{fj}|j=1,\dots,n\})^{-1} \text{ for } f= 1,\dots,h.$$

The radial DEA for environmental assessment is formulated as follows[12]:

$$\begin{aligned}
&\text{Maximize } \theta + \varepsilon\,[\textstyle\sum_{i=1}^{m} R_i^x d_i^{x-} + \sum_{r=1}^{s} R_r^g d_r^g + \sum_{f=1}^{h} R_f^b d_f^b]\\
&\text{s.t.} \quad \textstyle\sum_{j=1}^{n} x_{ij}\lambda_j + d_i^{x-} = x_{ik} \qquad (i=1,\dots,m),\\
&\quad \textstyle\sum_{j=1}^{n} g_{rj}\lambda_j - d_r^g - \theta g_{rk} = g_{rk} \qquad (r=1,\dots,s), \qquad (4.17)\\
&\quad \textstyle\sum_{j=1}^{n} b_{fj}\lambda_j + d_f^b + \theta b_{fk} = b_{fk} \qquad (f=1,\dots,h),\\
&\quad \textstyle\sum_{j=1}^{n} \lambda_j = 1,\\
&\quad \lambda_j \geq 0\ (j=1,\dots,n), \theta{:}\,URS\,, d_i^{x-} \geq 0\ (i=1,\dots,m),\\
&\quad d_r^g \geq 0\ (r=1,\dots,s)\ \&\ d_f^b \geq 0\ (f=1,\dots,h).
\end{aligned}$$

Under natural disposability, the efficiency score of the k-th DMU is determined as follows:

$$UEN = 1 - [\theta^* + \varepsilon\,(\textstyle\sum_{i=1}^{m} R_i^x d_i^{x*} + \sum_{r=1}^{s} R_r^g d_r^{g*} + \sum_{f=1}^{h} R_f^b d_f^{b*})] \qquad (4.18)$$

Were the in efficiency score (θ^*) and all slack variables are obtained from the optimality in the solution of (4.18).

As the non-radial environmental assessment approach the dual model for UEN radial environmental approach is formulated as follows

$$\begin{aligned}
&Min.\ \textstyle\sum_{i=1}^{m} v_i x_{ik} - \sum_{r=1}^{s} u_r g_{rk} + \sum_{f=1}^{h} w_f b_{fk} + \sigma\\
&s.t. \quad \textstyle\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r g_{rj} + \sum_{f=1}^{h} w_f b_{fj} + \sigma \geq 0 \quad (j=1,\dots,n),\\
&\quad \textstyle\sum_{r=1}^{s} u_r g_{rk} + \sum_{f=1}^{h} w_f b_{fj} = 1, \qquad (4.19)\\
&\quad v_i \geq \varepsilon R_i^x \qquad (i=1,\dots,m),\\
&\quad u_r \geq \varepsilon R_r^g \qquad (r=1,\dots,s),\\
&\quad w_f \geq \varepsilon R_f^b \qquad (f=1,\dots,h),\\
&\quad \sigma{:}\,URS.
\end{aligned}$$

[12] This model is proposed in previous researches, see, Sueyoshi and Goto (2012), Sueyoshi and Wang (2014)

The unified efficiency is determined by the following mathematical formulation:

$$UEN_v^R = 1 - [\sum_{i=1}^{m} v_i^* x_{ik} - \sum_{r=1}^{s} u_r^* g_{rk} + \sum_{f=1}^{h} w_f^* b_{fk} + \sigma^*]. \quad (4.20)$$

4.4.5 Unified Efficiency Under Managerial Disposability (UEM) Radial Model

By shifting from the natural disposability approach to the managerial disposability approach, which the priority is for environmental performance, then the operational performance comes in second. Then, the unified efficiency of the k-th DMU under managerial disposability is formulated as below:

$$\begin{aligned}
&\text{Maximize } \theta + \varepsilon\,[\sum_{i=1}^{m} R_i^x d_i^{x-} + \sum_{r=1}^{s} R_r^g d_r^g + \sum_{f=1}^{h} R_f^b d_f^b] \\
&\text{s.t.} \quad \sum_{j=1}^{n} x_{ij}\lambda_j - d_i^{x-} = x_{ik} \quad (i = 1, \dots, m), \\
&\sum_{j=1}^{n} g_{rj}\lambda_j - d_r^g - \theta g_{rk} = g_{rk} \quad (r = 1, \dots, s), \quad (4.21) \\
&\sum_{j=1}^{n} b_{fj}\lambda_j + d_f^b + \theta b_{fk} = b_{fk} \quad (f = 1, \dots, h), \\
&\sum^{n}{}_{j=1} \lambda_j = 1, \\
&\lambda_j \geq 0\ (j = 1, \dots, n), \theta{:}\ URS\ , d_i^{x-} \geq 0\ (i = 1, \dots, m), \\
&d_r^g \geq 0\ (r = 1, \dots, s)\ \&\ d_f^b \geq 0\ (f = 1, \dots, h).
\end{aligned}$$

Under the managerial disposability, the efficiency score of the k-th DMU is determined as follows:

$$UEM_k = 1 - [\theta^* + \varepsilon\,(\sum_{i=1}^{m} R_i^x d_i^{x*} + \sum_{r=1}^{s} R_r^g d_r^{g*} + \sum_{f=1}^{h} R_f^b d_f^{b*})]. \quad (4.22)$$

Where the sign before the slack variable results in the interpretations of natural disposability, and managerial disposability.

The dual model for UEM radial environmental approach is formulated as follows:

$$
\begin{aligned}
Min.\quad & -\sum_{i=1}^{m} v_i x_{ik} - \sum_{r=1}^{s} u_r g_{rk} + \sum_{f=1}^{h} w_f b_{fk} + \sigma \\
s.t.\quad & -\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r g_{rj} + \sum_{f=1}^{h} w_f b_{fj} + \sigma \geq 0 \quad (j=1,\ldots,n), \\
& \sum_{r=1}^{s} u_r g_{rk} + \sum_{f=1}^{h} w_f b_{fj} = 1, \\
& v_i \geq \varepsilon R_i^x \quad (i=1,\ldots,m), \qquad (4.23) \\
& u_r \geq \varepsilon R_r^g \quad (r=1,\ldots,s), \\
& w_f \geq \varepsilon R_f^b \quad (f=1,\ldots,h), \\
& \sigma : URS.
\end{aligned}
$$

The unified efficiency under UEM is determined by the following mathematical formulation:

$$UEM_v^R = 1 - [-\sum_{i=1}^{m} v_i^* x_{ik} - \sum_{r=1}^{s} u_r^* g_{rk} + \sum_{f=1}^{h} w_f^* b_{fk} + \sigma^*]. \qquad (4.24)$$

4.5 Position of The Thesis

In this thesis, the non-radial DEA environmental models under disposability concepts are utilized. The DEA environmental models have the advantages of addressing concepts related to the sustainability issues by separating the outputs into desirable and undesirable outputs, such as that discussed in the first central part of the thesis (Chapter 5). The disposability concepts applied in this thesis are considered as a new type of efficiency measure, which able to assess the operational and environmental performance for all DMUs in a combined form. The two concepts are known as natural disposability and managerial disposability, whereas in the natural disposability concept the company decreases the vector of inputs to decrease the vector of undesirable output, while attempts to increase the vector of desirable output as much as possible. On the other hand, in the managerial disposability concept the company increases the vector of inputs to decrease the vector of undesirable outputs, while attempts to increase the vector of desirable outputs as much as possible. The following figure illustrates the relation between the input and the two-type of outputs in the DEA environmental models:

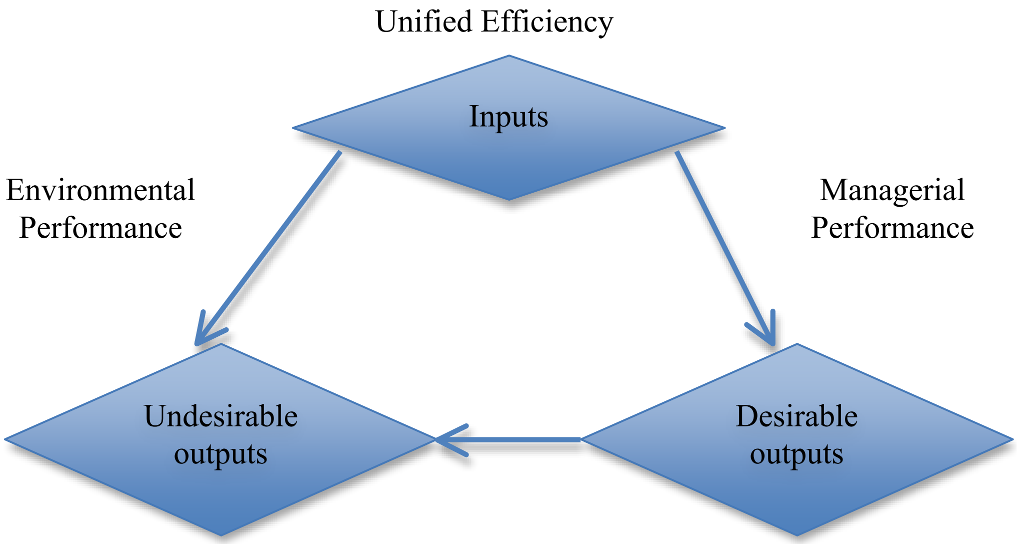

Figure 4.2 Relations Between the Production Factors in DEA Environmental Models

Further, in the second central part of the thesis (chapter 6), a combination of radial input-oriented DEA and DEA-discriminant analysis (DEA-DA) is utilized. The combination of the DEA as operational research and managerial approach and DA as a statistical approach gives a unique tool to predict the group membership in sampled data. Whereas, DEA categorized the DMUs into two groups (efficient and inefficient) based on their efficiency scores. Then, DEA-DA is used to evaluate all DMUs' operational efficiency scores and ranks to get an adjusted efficiency score for each DMU. The DEA-DA reduces the number of efficient DMUs and produces a single efficient DMU as an ideal performance to present an in-depth wild industry assessment based upon the adjusted efficiencies ranks.

Chapter 5

Vertical Structure and Efficiency Assessment of the US O&G Companies

5.1 Introduction

Environmentally conscious management is an inevitable monitor for companies in the energy sector due to their massive influence on total GHG emissions. In particular, the O&G industry whereas the O&G companies not only produce the necessary primary energy for economic growth and various petroleum products used as intermediate goods for many industries but also directly emit GHGs in the air. Therefore, reducing GHG emissions in the O&G industry should receive adequate attention from policymakers, corporate leaders, and individuals who are interested in environmental protection. However, many O&G companies have not necessarily adopted high standards for environmental protection or pollution reduction, even though they may have performed well on the operational efficiency side. Hence, an assessment of the operational and environmental performance of these companies is an essential first step to fight global warming and climate change for corporate sustainability and future sustainable development.

The US is one of the largest O&G producing countries in the world[13], and the world's 2nd largest contributor to energy-related GHG emissions, with a global share of 14.58%, after China with a 27.21% share (as of 2017)[14]. CO_2 emissions are a major component of GHG emissions, and the growth in CO_2 emissions is correlated with an increase in energy use for economic activities. Figure 5.1 depicts the US crude oil production and CO_2 emissions trends. The amount of CO_2 emissions has shown a relatively stable trend, around 5,000 to 6,000 million metric (MM) tons, while oil production has drastically increased in recent years, from approximately 1,800 million barrels in 2008 to 2,424 million barrels in 2015. Higher levels of oil shale production drive this increase. From Figure 5.1, it is evident that O&G companies have gained increasing importance in the US economy, while reducing CO_2 emission is still a pivotal issue for the US and for corporate sustainability in the O&G industry.

[13] See US Energy Information Administration (https://www.eia.gov/todayinenergy/detail.php?id=26352).
[14] See The Statistics Portal (https://www.statista.com/statistics/271748/the-largest-emitters-of-co2-in-the-world/).

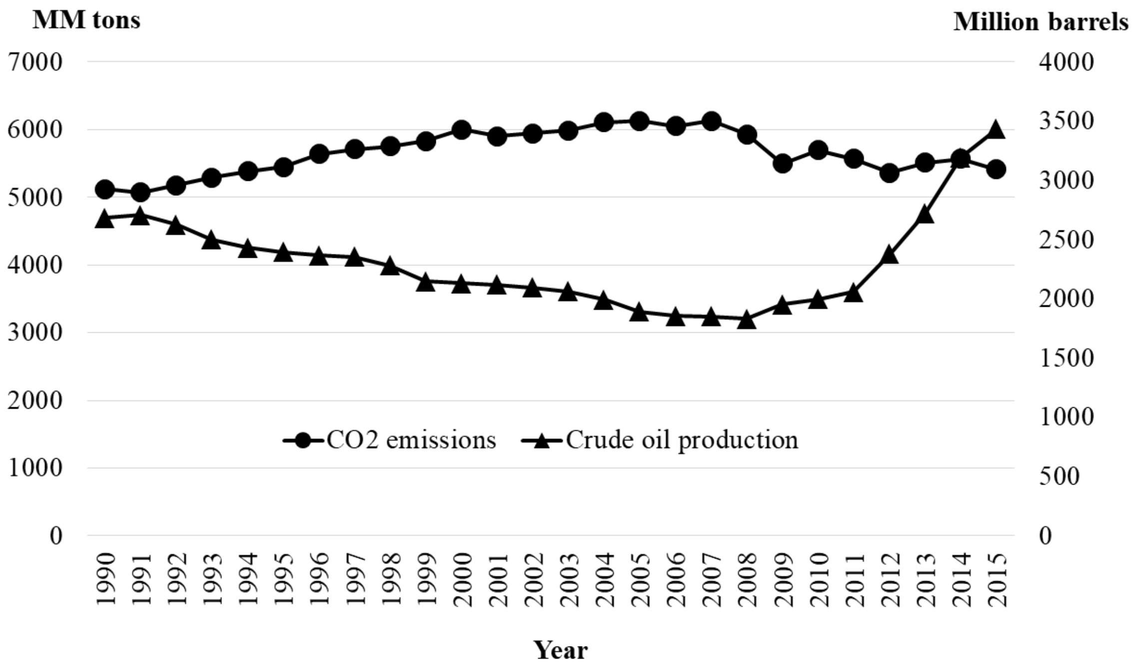

Figure 5.1: US Trend of Crude Oil Production and CO_2 Emissions; Note: MM tons represent million metric tons and Crude oil production includes oil shale

Source of Crude oil: https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=MCRFPUS1&f=A

Source of CO2: https://www.epa.gov/ghgemissions/inventory-us-greenhouse-gas-emissions-and-sinks-1990-2015

Accordingly, the US has conducted various measures to cut down on carbon pollution, such as the promotion of renewable energy and energy conservation (Executive Office of the President, 2013). According to the US Environmental Protection Agency (EPA), in 2017 the primary sources of GHG emissions in the US were the transportation sector (29%), electricity sector (28%), industrial sector (22%), commercial and residential sector (12%), and agriculture sector (9%), all of which amounted to 6,457 MM tons of CO_2 equivalent[15]. These numbers indicate that the largest source of GHG emissions is burning fossil fuels for electricity generation and transportation. Moreover, the O&G industry includes a wide range of operations and equipment: wells, natural gas gathering lines, processing facilities, storage tanks, and transmission and distribution pipelines. The industry is a primer source of emissions of methane, a potent GHG with a global warming potential more than 25 times that of CO_2. Therefore, energy and environmental issues are closely linked, and we need to

[15] See: https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions.

investigate environmental issues from the perspective of the energy use required for economic activities.

With the increasing momentum to explore and adjust new technology for energy efficiency and environmental protection, corporate leaders face pressure to carry out investment in technology and take necessary measures to promote corporate sustainability. Further, they also need to yield a sufficient return for shareholders. Therefore, corporate leaders always need to balance economic success and environmental protection, because such balance preserves companies' reputations and establishes concrete measures to survive in a competitive global market. Generally, consumers prefer environmentally conscious products and services and avoid products from firms with dirty images. Therefore, companies should plan to comply with the latest environmental regulations.

The purpose of this chapter[16] is to investigate the unified efficiency of a representative set of O&G companies in the US using a dataset comprising 34 companies between 2011-2015 and discuss policy implications for corporate sustainability. This chapter applies DEA to the data set. The sample contains seven major global petroleum companies (integrated firms) that operate in the US. The rest of the firms are independent American O&G companies. The companies can be categorized into two groups—integrated and independent. The integrated companies operate along the entire supply chain from upstream exploration to downstream retailing. Meanwhile, the independent ones engage only in upstream activities such as exploration, production, and development. Accordingly, I provide policy implications for their supply chain operations and carbon footprint by obtaining empirically unified efficiency measures.

The remainder of this chapter is structured as follows. Section 5.2 provides a literature review of the DEA studies applied to energy and environmental issues, particularly those related to O&G companies. Section 5.3 discusses the data set and the DEA model formulations. Section 5.4 presents empirical results on operational and environmental unified efficiency measures for the US O&G companies. Section 5.5 summarizes the results and suggests future research.

[16] This chapter is based upon the article: Atris, A.M., Goto, M., 2019. Vertical structure and efficiency assessment of the US oil and gas companies. Resource Policy. 36 (101437).

5.2 Literature Review

5.2.1 Selective DEA Studies Applied to the O&G Upstream Sector

This chapter summarizes selective DEA studies applied to the efficiency analysis of O&G upstream companies, as shown in Table 5.1. It describes and summarizes the methodology, inputs and outputs used to measure efficiency, as well as a brief description of each study.

Table 5.1 Selective DEA Studies Applied to Upstream O&G Companies[17]

Author(s)	Methodology	Description	Inputs	Outputs
Eller *et al.* (2010)	DEA & SFA (stochastic frontier analysis)	This study examined the revenue efficiency of national oil companies and private international oil companies in 2004. The data set consists of panel data of 78 firms all over the world. They found that the IOCs outperformed the NOCs because of their different objective perspectives.	- Number of employees - Oil reserves - Natural gas reserves	- Revenue
Managi *et al*. (2004)	DEA	Investigated the hypothesis that technological change has offset depletion for offshore O&G production in the Gulf of Mexico using a unique micro-level data set from 1947–1998. They found that the technological change has outpaced depletion and productivity has increased rapidly, particularly in most recent 5 years of the study period.	- Number of platforms - Ave. Platform size Number of exploration wells - Number of development wells - Average drilling distance for exploratory wells - Average drilling distance for development wells - Produced water -Weighted innovation index -Horizontal & directional drilling (exploratory) - Horizontal & directional drilling	- Oil production - Gas production

[17] The table is updated based upon table (1) in Atris and Goto (2019)

			(development)	
Sueyoshi and Goto (2012a)	DEA (non-radial) for environmental assessment	By using a data set of 19 national and international oil companies around the world over the period 2005-2009. This study theoretically explored how to measure Returns to Scale (RTS) under natural disposability and Damages to Scale (DTS) under managerial disposability to compare the performance of national oil companies with that of international oil companies.	- Oil reserves - Gas reserves - Operating coast - Number of employee	- Oil production - Gas production - CO_2 emissions
Sueyoshi and Goto (2012b)	DEA (non-radial) for environmental assessment	Compared the performance among 14 NOCs and 5 IOCs between 2005-2009. This study revealed that NOCs outperform IOCs in operational efficiency, while IOCs outperform NOCs in environmental efficiency.	- Oil reserves - Gas reserves - Operating coast - Number of employee	- Oil production - Gas production - CO2 emissions
Sueyoshi and Wang (2014)	DEA for environmental assessment, (Non-radial)	Examined the corporate sustainability development of 50 petroleum firms in the US in 2012. The study results indicated that the integrated companies outperform the independent companies because the former holds a large supply chain while the latter does not.	- AFD expenses - Total assets - Capital Expenditure - Number of employees - Net wells drilled	- Revenue - GHG emissions
Thompson *et al*. (1994)	DEA	Measured the efficiency and profitability of 14 oil companies (Majors) in the US for the years 1980-1987. They found that top-managers of major oil companies might capture the cost savings or profit ratio gains from making inefficient firms efficient.	- Total cost - Proved reserves in oil- equivalent units	- O&G exploration and improved recovery - O&G sales
Thompson *et al*. (1992)	DEA and assurance region analysis	Investigated technical efficiency for 45 independent O&G companies in the US over the period 1980-1986. They found that structural difference in the efficiency distributions has significantly different characteristics in the 1980-1982 periods than in the 1983-1986 period.	- Total production costs - Proven reserves (O&G) -Number of wells drilled	- Total production of crude oil and natural gas
Wang *et al*. (2018)	DEA for environmental assessment, Malmquist productivity index	Examined the carbon emission performance of a set of 31 independent O&G producers in the US for the period 2011–2015.	- Total assets - Operational expense - Wells drilled	- Revenue - Oil production - Gas production - Co_2 emission

Xun *et al.* (2011)	DEA	Evaluated efficiency of 17 NOCs on economic and social contribution in 2008. The results showed that NOCs had capability to take their economic, social, and political responsibilities when they sustained development.	- Operating margin - Rates of reserves - Exploitation of O&G - Return of investment (ROI)	- Average effective tax rate - Financial performance - Reserve rates of O&G - Energy security and employment

Eller *et al*. (2010) applied DEA and stochastic frontier estimation to a panel of 78 oil companies. They found that the IOCs outperformed the NOCs. The results pointed out that IOCs and NOCs had different objectives that influenced the firms' efficiency. Managi *et al*. (2004) measured TFP of offshore O&G production in the Gulf of Mexico between 1947 and 1998. The authors applied DEA to compute productivity and decomposed it into technological change, efficiency change, and scale change. They found that productivity declined for the first 30 years of the study period, but technological change outpaced depletion, and, as a result, productivity has increased rapidly, particularly in the last 5 years of the study period. Sueyoshi and Goto (2012a) measured petroleum companies' returns to scale (RTS) and damages to scale (DTS). Based on their results, the authors discussed two alternative strategies for petroleum companies to reduce CO_2 emissions produced by their operations. Using the same data set, Sueyoshi and Goto (2012b) discussed desirable and undesirable output unification and proposed a non-radial DEA model that is reformulated for environmental assessment. They applied the model to a data set comprising NOCs and IOCs and compared the performance between the two groups. The results indicated that NOCs outperform IOCs in operational efficiency, while IOCs outperform NOCs in environmental efficiency. Sueyoshi and Wang (2014) measured two types of unified efficiency for US integrated and independent petroleum companies using non-radial DEA models. They used GHG emissions as an undesirable output. The results revealed that the integrated companies outperformed the independent ones due to their longer supply chain. The authors concluded the longer supply chain system, covering both upstream and downstream business functions, enhanced corporate sustainability in the US. Thompson *et al*. (1994)

analyzed DEA profit and efficiency measures for 14 major oil companies applying DEA and AR methods to a data set from 1980 to 1987. The DEA measures partitioned the firms into low and high achievers, and the discriminate analysis supported the partition. They found that top-managers of major oil companies might capture the cost savings or profit ratio gains from making inefficient firms efficient. Thompson *et al*. (1992) analyzed the productive efficiencies of 45 randomly sampled O&G independent firms from 1980 to 1986 using DEA, equipped with assurance region (AR) principles. AR is often used for multiplier restrictions in DEA. They found that the distribution of the DEA efficiency measures exhibited significantly different characteristics in the 1980-1982 period compared to the 1983-1986 period. Wang *et al* (2018) investigated the carbon emission performance of a set of 31 independent oil and natural gas producers in the US between 2011and 2015, under two types of disposability (natural and managerial. They found that under natural disposability the performance has improved from 2012 to 2015. On the other hand, under managerial disposability, the results exhibit significantly higher dispersions than the results under natural disposability, and there is an industry-wide loss of efficiency in terms of TE. Xun *et al*. (2011) studied NOCs' roles in the economy and society based on profitability. They applied the DEA method to evaluate the efficiency of NOCs' economic and social contributions. The results showed that NOCs had the capability to take their economic, social, and political responsibilities.

5.2.2 Contribution to The literature

After a careful review of previous studies on O&G companies, only a few studies use the DEA environmental assessment by applying "disposability concepts," are found. The concepts are important to discuss firms' managerial efforts to protect the environment. To fill the gap between the conceptual importance and scarcity of the empirical research, this chapter applies the DEA environmental assessment to a unique balanced panel data set, comprising 34 O&G companies in the US from 2011 to 2015. This chapter can be positioned as an extension of Sueyoshi and Wang (2014), because their study analyzed cross-sectional data for 50 US O&G companies in 2012.

5.3 US O&G Industry Regulations

Recently, the US has become one of the largest O&G producers in the world, so the law regulating the industry has become more critical than before. The institutional design of regulation in the US is different from any other country because all companies in the US are private, and there are no NOCs, as opposed to many other countries. Besides, the O&G laws in the US are classified into federal and state regulations.

5.3.1 Federal regulation

In the early 1980s, the US EPA, state, and local governments launched an array of regulations applicable to drilling, natural gas processing, storage, compression, dehydration, and pipeline transportation. For instance, the EPA regulations that are intended to cut down and control industry GHG emissions from O&G drilling activities are described below:

1. New Source Performance Standards (NSPS) regulates volatile organic compounds (VOCs) and other particulate pollutants that are emitted in the hydraulic fracturing process and specific equipment used in upstream and midstream operations by the O&G industries. In particular, it regulates VOCs emissions from gas wells, centrifugal compressors, storage vessels, and leaking ingredients, as well as sulfur dioxide (SO_2) emissions in onshore natural gas processing plants[18]. This rule determines cost-effective performance standards for: a) gas wells, which covers only gas wells that work onshore to produce natural gas; b) fractured and refractured gas wells, which requires owners and operators to reduce VOCs emissions from well completions, using reduced emissions completions (RECs) or green completions[19]; and c) storage vessels, for which natural gas transmission and storage segments with emissions equal to or greater than 6 tons per year (tpy) should achieve at least 95% reduction in VOCs emissions.

2. National Emission Standards for Hazardous Air Pollutants (NESHAP). The NESHAP program regulates the primary stationary sources standards for hazardous air pollutants (HAPs). The Clean Air Act (CAA) determines the

[18] 40 CFR (Code of Federal Regulations) Part 60-Standards of performance for new stationary sources.
[19] EPA Fact Sheet, "Overview of Final Amendments to Air Regulations for the Oil and Natural Gas Industry," available at http://www.epa.gov/airquality/oilandgas/pdfs/2012041 7fs.pdf.

emissions sources of 10 tpy for any HAPs or 25 tpy for a combination of HAPs[20]. Furthermore, the NESHAP requires a Maximum Achievable Control Technology (MACT)[21], which means operators/owners or companies must reduce emissions to the maximum degree achievable. The NESHAP only affects glycol dehydrators, storage vessels, tanks, equipment leaks at gas processing plants area sources - Triethylene Glycol (TEG) dehydrators, and testing requirements in O&G segments. This standard requests information on HAPs emissions' in oil and natural gas production, transmission, and storage segments of the oil and natural gas sector.

3. EPA requires Air Emissions Reporting Requirements (AERR) from the states and local agencies to collect and submit their emissions data to EPA's Emissions Inventory System (EIS), which helps the EPA to build the National Emissions Inventory (NEI) and estimate the total emissions in the states[22].

4. EPA mandates that operators, owners, and all facilities that emit at least 25,000 metric tpy of GHG submit a report of GHG gases[23]. On the other hand, the Department of Energy (DOE) established Voluntary GHG Reporting[24], to motivate the government and non-government agencies, public and/or private entities, and households to submit their annual GHG emissions report. These kinds of reports will provide an authoritative record of all entities' contributions toward reducing their GHG emissions.

The US high standards put an extra burden on O&G companies that would increase total costs of the companies to meet regulations. The companies need to invest more in technology, e.g., using high standards wells to reduce the emissions through the drilling process and may consider to integrate vertically to be efficient and retain their market share in a competitive and regulated market.

[20] 42 U.S. Code § 7412-Hazardous air pollutants, (a)(1).
[21] 40 CFR Part 63-National emission standards for hazardous air pollutants for source categories.
[22] 40 CFR Part 51-Requirements for preparation, adoption, and submittal of implementation plans.
[23] 40 CFR Part 98-Mandatory greenhouse gas reporting.
[24] 10 CFR Part 300-Voluntary greenhouse gas reporting program: General guidelines.

5.3.2 State level regulations

O&G regulations enacted in individual states have their own regulatory agencies or bodies that manage and protect the rights of adjacent landowners by regulating the distance between oil wells and property lines. Also, they regulate health and safety issues and prevent waste. The state regulations differ over time and from state to state and include, e.g., hydraulic fracturing, drilling, well closure, O&G production, and leasing. As a few examples, this chapter selects Texas, Colorado, and North Dakota to explain state-level regulations[25].

- ***Texas***

The Railroad Commission of Texas (RRC) enforces Texas O&G regulations. Moreover, the Texas Commission on Environmental Quality (TCEQ), the state's environmental agency, has a significant role in the areas of air & water quality, and surface water management. The RRC is responsible for preventing waste of natural resources and protects the owner's rights as well. For example, spacing rules stipulate no well is drilled nearer than 467 feet to "any property line, lease line or subdivision line."[26] Also, no well for oil, gas, or geothermal resources is drilled nearer than 1,200 feet to "any well completed in or drilling to the same horizon on the same tract or farm." Pooled development rules are stipulated under Statewide Rule 40[27].

In 2012, the RRC began enforcing Hydraulic Fracturing Chemical Disclosure Requirements under statewide rule 29[28], as one of the most comprehensive rules in the nation for the disclosure of chemical ingredients used in hydraulic fracturing fluids. The rule requires operators to declare chemical components and water volumes utilized in hydraulic fracturing treatments. In January of 2011, the TCEQ announced rules covering 23 provinces in and around the Barnett Shale[29].

[25] The reason for the selection is that most of the firms studied are located in Texas and Colorado, and these three states have productive oil fields in the US. For example, Texas is the largest O&G producer with two main oil fields, Permian and Eagle Ford Shale. North Dakota is the second largest O&G producer in the US, with the Bakken oil field. Colorado is one of the top ten O&G producers in the US and has the Niobrara Shale formation in the Denver and Wattenberg Gas Field.

[26] Texas Administrative Code, Title 16: Economic regulation, Part 1: Railroad commission of Texas, Chapter 3: O&G division, §3.37: Statewide spacing rule.

[27] Texas Administrative Code, Title 16: Economic regulation, Part 1: Railroad commission of Texas, Chapter 3: O&G division, §3.40: Assignment of acreage to pooled development and proration units.

[28] Texas Administrative Code, Title 16: Economic regulation, Part 1: Railroad commission of Texas, Chapter 3: O&G division, §3.29: Hydraulic fracturing chemical disclosure requirements.

[29] https://www.tceq.texas.gov/permitting/air/permitbyrule/subchapter-o/oil_and_gas.html.

The rules made air quality standard permits necessary for the operation of new stationary facilities at a site where natural gas and petroleum fluids are handled[30]. In line with air quality standards, TCEQ regulates the emissions of VOCs from stationary sources to meet National Ambient Air Quality Standards for ozone[31].

- ***Colorado***

The Colorado O&G Conservation Commission (COGCC) regulates the O&G production in the state to save correlative rights in every pool, to prevent waste, and to protect the environment. For instance, the well location rules relative to the closest property boundary depends on whether the well is less than 2,500 feet in depth or higher[32]. In other words, they vary based on whether the hydrocarbon source is oil or gas.

After April 1, 2012 COGCC utilized the Hydraulic Fracturing Chemical Disclosure Requirements under rule 205A that required the operator to declare the conclusion of a hydraulic fracturing treatment to FracFocus (https://fracfocus.org/), e.g., the actual vertical depth of the well, the longitude and latitude of the wellhead, and water volume used in the hydraulic fracturing treatment as well as any additive hydraulic fracturing[33]. Furthermore, Colorado declared the first significant state methane rules in the US in 2014 as a response to leak detection and repair (LDAR) programs. Those rules desired controls for storage tanks and promoted LDAR for upstream O&G operations. Furthermore, the rules require owners and operators to inspect components at the natural gas compressor and well production tools for leaks, with infrared cameras to identify and fix leaks. The Air Quality Control Commission (AQCC) in Colorado released regulations for VOCs from O&G operations such as storage tanks to mitigate the impact of these emissions on the ozone layer[34].

- ***North Dakota (ND)***

The ND Industrial Commission, Department of Mineral Resources, O&G Division supervises the O&G industry in the state. Moreover, it promotes the development, production, and utilization of O&G resources in a manner that it prevents waste and protects all parties' rights. An example of ND O&G regulations to

[30] Air Quality Permit, supra note 204, at 103.
[31] Texas Administrative Code, Title 30, Chapter 115, that are part of the State Implementation Plan strategy to meet the National Ambient Air Quality Standards for ozone.
[32] Code of Colorado Regulations, § 404-1 (318) (a) (b).
[33] Code of Colorado Regulations, § 404-1 (205A) (1) (2).
[34] Code of Colorado Regulations, 5, 1001-9, § XII.

keep correlative landowner rights. These include, e.g., that oil wells with a minimum spacing unit size of 40 acres be located not less than 500 feet (152.4 meters) from the property boundary. Moreover, gas wells that have a minimum spacing unit size of 160 acres shall be located not less than 500 feet[35] away.

The ND regulations also addressed hydraulic fracture stimulation, with rules that cover the hydraulic fracture stimulation performed (1) through a frac string run inside the intermediate casing string, (2) through an intermediate casing string[36]. In addition, the operators, owners, or service companies are required to apply their chemical disclosure to FracFocus, like in other states.

With regard to safety regulations, the ND Industrial Commission requires that all oil wells should be cleaned in a tank or a pit, not less than 40 feet from the derrick crane floor and 150 feet from any fire risk. In addition, 500 feet from an occupied residence is required to install any drill or production equipment, except if agreed to in writing by the owner of the residence or by the commission[37].

5.4 Hypotheses

As shown in Section 5.3, there are various environmental laws and regulations imposed on the O&G industry. These become constraints on free business operations and may limit companies' profits, but corporate leaders balance operational and environmental efficiencies to improve both. Otherwise, companies may suffer damage to their corporate value from legal violations and unexpected incidents that cause environmental destruction.

This chapter supposes two null hypotheses based on previous studies and discussions of DEA applications to O&G companies. These hypotheses are tested in the empirical analysis.

[1st hypothesis]

The study period covers the years under the Obama administration. Since the US did not ratify the Kyoto Protocol under the Bush administration, various measures to reduce GHG emissions were conducted through state-level policy. The Obama administration was in favor of energy security and environmental protection policy.

35 ND Administrative Code 43-02-03-18(1).
36 ND Administrative Code 43-02-03-27.1.
37 ND Administrative Code 43-02-03-28.

President Obama's Climate Action Plan proposed a reduction in GHG emissions and defined various policy goals to tackle global warming and climate change problems. In line with these policy goals, the US EPA proposed many laws and regulations directly related to drilling activities in the O&G industry to cut down and control GHG emissions. Although the policy goals of the Obama administration and the EPA stretched beyond 2020, this chapter assumes that temporal improvement in the operational and environmental unified efficiency measures for O&G companies over the study period arise under the Obama administration, with various other state-level environmental protection measures, and EPA policy. Therefore, the first null hypothesis of this chapter is described as follows:

H_0: Efficiency measures invariantly distributed over five years. There are no statistically significant changes to the efficiency levels over time.

[2nd hypothesis]

Integrated companies operate supply chain functions or downstream functions, which include the refining of crude oil, processing, marketing, and distribution. Downstream companies sell O&G products to consumers. These downstream functions provide companies with the opportunity to directly connect with consumers by implementing higher standards for environmental protection in an effort to secure better branding as good corporate citizens. For example, Laari *et al*. (2016) discussed direct and indirect relationships between firms' performance and customer-driven green supply chain management among 119 Finnish manufacturing firms. Wang *et al*. (2018) examined the influence of cost and customer drivers on internal and external green practices and their contribution to environmental performance based on 246 companies across the world. Gualandris and Kalchschmidt (2014) examined how sustainability supply chain management is affected by customer pressure and innovativeness in 77 Italian manufacturing firms. Furthermore, Zhu *et al*. (2017) referred to the role of customer relational governance in environmental and economic performance enhancement in relation to green supply chain management in China.

In addition, the management of these firms is implemented globally, meaning they need to comply with higher efficiency standards on the international level. On the other hand, independent companies do not have such retail functions. They only focus on upstream functions, which include searching for potential underground or underwater crude oil and natural gas fields, drilling exploratory wells, and subsequently drilling and operating the wells that bring the crude oil or raw natural gas to the surface. Based on the different characteristics of upstream and downstream functions, we assume there are some differences in their efficiency levels, so the second null hypothesis is as follows:

H_0: Efficiency measures invariantly distributed between independent and integrated companies. There is no difference between their efficiency levels.

5.5 Methodology

5.5.1 Data

The dataset used in this chapter comprises 34 O&G companies in the US energy sector. All of them were included in the New York Stock Exchange (NYSE) Energy Index for the time period 2011-2015[38]. This chapter uses one desirable output, five inputs, and one undesirable output for the DEA application. The undesirable output is the amount of CO_2 emissions from the onshore exploration and production sectors. CO_2 emissions are generated directly through drilling activities and fossil fuel combustion and indirectly through well leaks and venting. Using CO_2 emissions as an undesirable output, this chapter assesses the unified efficiency for environmental protection among US O&G companies.

The amount of CO_2 emissions source is from the EPA's GHG Reporting Program (2012-2016), which corresponds to the emission of 2011-2015[39]. The emission data set is reported at the facility level, not at a company level. Therefore, we collect emissions data for all onshore O&G production sites and then aggregate them to the firm level. The number of wells for companies was collected from their annual reports, which counts only the onshore wells drilled in the US. This chapter classified the amount of capital expenditures or investment costs into two components: "proved, unproved properties" and "exploration, development and others." The capital expenditures data were obtained from Ernst & Young (2012-2016), which corresponds to the period from 2011-2015. The data set is summarized below.

[38] New York Stock Exchange （https://www.nyse.com/data/transactions-statistics-data-library#monthly_consolidated_by_volume_2015） （https://tools.ceres.org/resources/tools/sec-sustainability-disclosure/@@ce-search-s3）
[39] Environmental Protection Agency (https://www.epa.gov/ghgreporting)

5.5.1.1 [Five Inputs]

- **Number of employees:** This variable is a typical factor often used in production economics, which generally defines inputs comprising of labor and capital[40]. This variable is also considered a proxy for firm size. Larger numbers of employees may increase the labor cost burden for the company leading to operational inefficiencies. On the other hand, larger firms may have access to various resources and technologies to adapt their environmental policies and to mitigate GHG emissions.
- **Proved, unproved properties:** This variable consists of capital expenditures consisting of proved and unproved property acquisition costs. More capital expenditures for proved, unproved properties may increase the capital cost burden for the company and may lead to operational inefficiencies. On the other hand, capital expenditures indicate operating liquidity or cash holdings and represent a firm's ability to acquire assets.
- **Exploration, development, others:** This variable is the other component of capital expenditures and accounts for the costs spent on exploring the property, including drilling exploratory wells. Future benefits can only be acquired if gas or oil is found. Higher capital expenditures increase future production capability, but also may incur excessive cost burdens if the firm piles up inactive wells. Larger capital expenditures may lead to more investment for environment protection to mitigate CO_2 emissions.
- **Total assets:** This variable expresses the final amount of all gross investments, cash and equivalents, receivables, and other assets as presented on the balance sheet. Higher total assets generally indicate higher production and service capability for the firm. On the other hand, if the asset base is too large compared to the firm's production or revenue, assets may induce inefficiencies. They are used as another indicator of company size.

- **Number of net wells drilled:** This variable illustrates the number of wells drilled by a company. More wells imply higher production capability and higher opportunity to yield profit. At the same time, if a company maintains too many unproductive or inactive wells, this can reduce efficiency.

[40] The other four inputs are classified as capital inputs.

5.5.1.2 [One desirable output]

- Operational revenue: This is the total amount of revenue that was received from the sale of O&G. Larger revenue generally implies higher profits and business success for the company. This variable also determines the company's operational size. On the other hand, if a firm incurs substantial costs, it may be inefficient even if it has a large revenue stream.

5.5.1.3 [One undesirable output]

- CO_2 emissions: This variable measures the amount of CO_2 emissions from the company's onshore exploration and production sectors. Investments in prevention policies may change with the scale of current and future emissions.

Table 5.2 Production Factors for Independent and Integrated Companies on Averages

Outputs & Inputs		Undesirable output	Desirable output	Inputs				
Production factors		CO2 emissions	Operating revenue	Total assets	Employees	Number of wells drilled	Proved, unproved properties	Exploration, development & others
Year	Unit	Metric tons	Millions $	Millions $	Number of employees	Number of wells	Millions $	Millions $
2011	Independent	660,472	36,144	25,151	5,079	388	953	3,110
	Integrated	510,102	226,680	179,323	48,451	420	4,757	13,756
2012	Independent	606,274	37,912	25,553	4,949	418	1,221	2,789
	Integrated	789,468	222,500	187,650	47,888	470	1,344	5,646
2013	Independent	749,735	24,161	26,962	5,119	384	304	2,753
	Integrated	947,566	213,975	194,196	47,101	504	281	5,869
2014	Independent	885,865	142,575	28,859	4,841	359	1,404	3,115
	Integrated	916,447	199,148	192,010	46,192	496	386	6,058
2015	Independent	788,433	174,874	21,503	3,866	246	418	2,049
	Integrated	841,320	127,377	183,264	44,017	412	187	4,989
All	Independent	738,156	83,471	25,606	4,771	359	860	2,763
	Integrated	800,981	197,936	187,289	46,730	460	1,391	7,264

Table[41] 5.2 presents the data's descriptive statistics. Avg., S.D., Min., and Max. denote the average, standard deviation, minimum, and maximum, respectively.

On average, integrated companies had higher production factors than independent companies during the study period between 2011 and 2015, with the exception of CO_2 emissions in 2011 and proved, unproved properties in 2014 and

[41] Source: Atris and Goto (2019)

2015, when independent firms had higher indicators than the integrated firms. For example, the average CO_2 emissions produced by independent companies were 660,472 metric tons, while integrated companies produced 510,102 metric tons in 2011. The average number of wells drilled was higher for integrated companies than for independent companies over the period 2011-2015. However, the most active driller, Occidental Petroleum with 1,411 net wells drilled in 2012, is an independent company.

Capital expenditures consist of those for proved, unproved properties, and for exploration, development & others. Both variables show relatively large year-over-year changes since they are influenced by various factors such as the corporate investment strategy, the firms' cash holdings, and macro-economic behavior. In particular, capital expenditures on proved, unproved properties show drastic changes for both independent and integrated companies. This is probably because the expenditures are largely influenced by the abovementioned factors. In addition, there is clear evidence that integrated companies have larger investment budgets than independent firms.

5.5.2 Models

This chapter utilized the DEA non-radial models for environmental assessment that mentioned in detail in chapter 4 in section (4.4.1) under two disposability concepts UEN and UEM. The mathematical form of the DEA non-radial models are as follows:

Production technology under natural disposability ($P^N(X)$) and managerial disposability ($P^M(X)$) is expressed by equation (4.4) and the differences between the two disposability concepts are their respective inequality constraints. For natural disposability, or $p^N(X)$, the input constraint is $X \geq \sum_{j=1}^{n} X_j\lambda_j$, while for managerial disposability, or $P^M(X)$, the constraint is $X \leq \sum_{j=1}^{n} X_j\lambda_j$. The unification of the two-production possibility sets results in the following output set, where ∪ stands for a union set.

$$P^U(X)=P^N(X) \cup P^M(X). \qquad (4.5)$$

If we assume that the unified output set is applied to the DEA formulation, we need to describe the model under natural and managerial disposability[42]. This chapter does not discuss such a unification process further, but rather we measure the operational and environmental performance of firms using two separate models described below.

5.5.2.1 Unified Efficiency Under Natural Disposability (UEN)

The following three data ranges are used for the objective functions related to each production factor, inputs, desirable outputs, and undesirable outputs, respectively:

$$
\begin{aligned}
R_i^x &= (m+s+h)^{-1}(\{x_{ij}|j=1,\dots n\} - \{x_{ij}|j=1,\dots,n\})^{-1} \quad \text{for } i = 1,\dots,m,\\
R_r^g &= (m+s+h)^{-1}(\{g_{rj}|j=1,\dots n\} - \{g_{rj}|j=1,\dots,n\})^{-1} \quad \text{for } r = 1,\dots,s, \quad (4.7)\\
R_f^b &= (m+s+h)^{-1}(\{b_{fj}|j=1,\dots n\} - \{b_{fj}|j=1,\dots,n\})^{-1} \quad \text{for } f = 1,\dots,h.
\end{aligned}
$$

Radial models are generally more popular in DEA studies, but non-radial models are also used in DEA applications as shown in Table 5.1[43]. A non-radial DEA model to measure the level of UEN of the k-th DMU with natural disposability is described as follows.

$$
\begin{aligned}
\text{Maximize } & \textstyle\sum_{i=1}^{m} R_i^x d_i^x + \sum_{r=1}^{s} R_r^g d_r^g + \sum_{f=1}^{h} R_f^b d_f^b\\
\text{s.t. } & \textstyle\sum_{j=1}^{n} x_{ij}\lambda_j + d_i^x = x_{ik} \quad (i=1,\dots,m),\\
& \textstyle\sum_{j=1}^{n} g_{rj}\lambda_j - d_r^g = g_{rk} \quad (r=1,\dots,s),\\
& \textstyle\sum_{j=1}^{n} b_{fj}\lambda_j + d_f^b = b_{fk} \quad (f=1,\dots,h), \qquad (4.8)\\
& \textstyle\sum_{j=1}^{n} \lambda_j = 1,\\
& \lambda_j \ge 0\ (j=1,\dots,n),\ d_i^x \ge 0\ (i=1,\dots,m),\\
& d_r^g \ge 0\ (r=1,\dots,s)\ \&\ d_f^b \ge 0\ (f=1,\dots,h).
\end{aligned}
$$

Here, x_{ij} is the observed value of the i-th input $(i = 1,\dots,m)$ on the j-th DMU $(j = 1,\dots,n)$; g_{rj} is the observed value of the r-th desirable output $(r = 1,\dots,s)$ on the j-th DMU $(j = 1,\dots,n)$; b_{fj} is the observed value of the f-th undesirable output $(f = 1,\dots,h)$ on the j-th DMU $(j = 1,\dots,n)$; d_i^x is a slack variable related to the i-th

[42] See Model (1) in Sueyoshi and Goto (2012a) for detailed explanation of the concepts and mathematical formulations under natural and managerial disposability.

[43] Tone (2001) proposed a new type of non-radial DEA model that is called SBM (slacks-based measure). SBM has been widely applied to energy and environment studies, e.g., Zhang and Choi (2013).

input $(i = 1, \ldots, m)$; d_r^g is a slack variable related to the r-th desirable output $(r = 1, \ldots, s)$; d_f^b is a slack variable related to the f-th undesirable output $(f = 1, \ldots, h)$; $\lambda = (\lambda_1, \ldots, \lambda_n)^T$ which expresses the unknown "intensity" or "structural" variables where T represents a vector transpose.

The UEN is obtained by subtracting the level of inefficiency from unity. The inefficiency in the objective function is expressed in parenthesis.

$$UEN = 1 - [\sum_{i=1}^{m} R_i^x d_i^{x*} + \sum_{r=1}^{s} R_r^g d_r^{g*} + \sum_{f=1}^{h} R_f^b d_f^{b*}] \qquad (4.9)$$

Here, all slack variables with asterisks are identified at the optimality of Model (4.8).

5.5.2.2 Unified Efficiency Under Managerial Disposability (UEM)

The following non-radial model measures the level of UEM of the k-th DMU. The only difference between Models (4.8) and (4.13) is the sign of the input slack variable (d_i^x) at the first constraint equation. The difference carries large implications.

$$\begin{aligned}
\text{Maximize} \quad & \sum_{i=1}^{m} R_i^x d_i^x + \sum_{r=1}^{s} R_r^g d_r^g + \sum_{f=1}^{h} R_f^b d_f^b \\
\text{s.t.} \quad & \sum_{j=1}^{n} x_{ij}\lambda_j - d_i^x = x_{ik} \quad (i = 1, \ldots, m), \\
& \sum_{j=1}^{n} g_{rj}\lambda_j - d_r^g = g_{rk} \quad (r = 1, \ldots, s), \qquad (4.13) \\
& \sum_{j=1}^{n} b_{fj}\lambda_j + d_f^b = b_{fk} \quad (f = 1, \ldots, h) \\
& \sum_{j=1}^{n} \lambda_j = 1, \\
& \lambda_j \geq 0 \ (j = 1, \ldots, n), \ d_i^x \geq 0 \ (i = 1, \ldots, m), \\
& d_r^g \geq 0 \ (r = 1, \ldots, s) \ \& \ d_f^b \geq 0 \ (f = 1, \ldots, h).
\end{aligned}$$

As with the UEN, the k-th DMU's degree of UEM is measured by subtracting the inefficiency, or the value of the equation in parenthesis, from unity.

$$UEM = 1 - [\sum_{i=1}^{m} R_i^x d_i^{x*} + \sum_{r=1}^{s} R_r^g d_r^{g*} + \sum_{f=1}^{h} R_f^b d_f^{b*}] \qquad (4.14)$$

5.6 Empirical Results

Table 5.3 indicates the UEN results for the examination period between 2011 and 2015. Chesapeake Energy Corporation had the worst efficiency among independent companies (0.3630) in 2013, although the company achieved full efficiency (unity) in 2011[44]. The same trend of efficiency is observed for BHP Billiton Group. The low performance of Chesapeake Energy Corporation after 2011 may be related to the EPA fine that was imposed on the company due to an environmental regulation violation that might have negatively affected the company's revenue[45]. In addition, Exxon Mobil Corporation shows the worst performance among integrated companies during the observation period, with an efficiency of only 0.3222 in 2011. The company shows low operational efficiencies over the five-year period. On the other hand, three companies–two independent (PDC Energy, Inc., and Ultra Petroleum Corporation) and one integrated (Chevron Corporation) have the highest efficiency measures (unity) for all five years.

Table 5.3 Unified Efficiency under Natural disposability (UEN)

Company name / Year	2011	2012	2013	2014	2015
Independent companies					
Anadarko Petroleum Corporation	0.5830	0.7375	0.5102	0.6528	0.6933
Antero Resources LLC	1.0000	1.0000	0.9128	1.0000	1.0000
Apache Corporation	0.6833	0.6379	1.0000	0.6477	0.7965
BHP Billiton Group	1.0000	0.4929	0.5484	0.6498	0.7150
Cabot Oil & Gas Corporation	1.0000	0.9673	0.8318	0.9019	0.9506
Chesapeake Energy Corporation	1.0000	0.4322	0.3630	0.6175	0.6958
Cimarex Energy Co.	0.8939	0.9314	0.7799	0.8607	0.9272

[44] The results of Wang and Li (2018) and this chapter differ somewhat. For example, UEN results of Chesapeake Energy Corporation had full efficiency (unity) in 2013 and 0.635 in 2011, which were not consistent with results obtained in this chapter. As for the Chesapeake Energy Corporation, this chapter showed that UEN results had the worst efficiency among independent companies, with an efficiency score of 0.3630 in 2013, although the company achieved full efficiency (unity) in 2011.

[45] U.S. Energy Information Administration, https://yosemite.epa.gov/opa/admpress.nsf/0/82EF516757FCD5DD85257C4600814C2B

Conoco Phillips	0.5122	0.5554	0.4766	0.5690	0.5710
Continental Resources, Inc.	0.7834	0.7702	0.6753	0.7700	0.7820
Denbury Resources Inc.	0.9311	0.8781	1.0000	1.0000	1.0000
Devon Energy Corporation	0.6668	0.6567	0.6298	0.6016	0.6639
EnCana Corporation	0.7708	0.9005	0.7952	0.7319	0.9038
Energen Corporation	0.8107	0.9423	0.8306	0.9256	1.0000
EOG Resources, Inc.	0.5932	0.6162	0.4643	0.5717	0.6574
EQT Corporation	0.8948	0.9648	0.8163	0.8621	0.8611
Newfield Exploration Company	0.7789	0.9416	0.7769	0.8598	0.9030
Noble Energy, Inc.	0.7456	0.9138	0.7379	0.8251	0.6773
Occidental Petroleum Corporation	0.5890	0.5501	0.5763	0.7121	0.8234
PDC Energy, Inc.	1.0000	1.0000	1.0000	1.0000	1.0000
Pioneer Natural Resources Company	0.8502	0.8499	0.7385	0.8230	0.9003
QEP Resources, Inc.	1.0000	0.8134	0.7890	0.8332	0.8928
Range Resources Corporation	0.8812	0.9338	0.8235	0.8897	0.9567
SM Energy Company	1.0000	0.9325	0.7768	0.8515	0.9253
Southwestern Energy Company	0.8337	0.9116	0.7598	0.7613	0.8371
Ultra Petroleum Corporation	1.0000	1.0000	1.0000	1.0000	1.0000
Whiting Petroleum Corporation	0.8959	0.9254	0.7271	0.7118	0.8343
WPX Energy, Inc.	1.0000	0.9170	0.7908	0.9094	0.7926
Avg.	0.8407	0.8212	0.7456	0.7977	0.8430
Max.	1.0000	1.0000	1.0000	1.0000	1.0000
Min.	0.5122	0.4322	0.3630	0.5690	0.5710
S.D.	0.1519	0.1685	0.1680	0.1347	0.1236
Integrated companies					

BP PLC	0.4101	0.5489	0.5732	0.5816	1.0000
Chevron Corporation	1.0000	1.0000	1.0000	1.0000	1.0000
Exxon Mobil Corporation	0.3222	0.3793	0.6280	0.3618	0.3250
Hess Corporation	0.7361	0.7929	0.7034	0.8611	0.8434
Marathon Oil Corporation	0.7002	0.6916	0.6685	0.7493	0.8033
Murphy Oil Corporation	1.0000	0.9124	0.7701	0.8762	0.9494
Royal Dutch Shell plc	0.4560	1.0000	1.0000	1.0000	1.0000
Avg.	0.6607	0.7607	0.7633	0.7757	0.8459
Max.	1.0000	1.0000	1.0000	1.0000	1.0000
Min.	0.3222	0.3793	0.5732	0.3618	0.3250
S.D.	0.2554	0.2183	0.1600	0.2164	0.2252

(a) Max., Min. and S.D. stands for Maximum, Minimum and Standard Deviation.

(b) Source: Atris and Goto (2019)

On average, the independent companies outperformed in 2011, 2012 and 2014 with efficiency scores of 0.8407, 0.8212, and 0.7977, respectively, while the integrated companies outperformed in 2013 and 2015 with average efficiency scores of 0.7633 and 0.8459, respectively. Therefore, this chapter cannot clearly determine which group of companies has superior operational efficiency. In addition, it is interesting to note that integrated companies' standard deviations are larger for all years except for 2013, even though the data set contains more independent than integrated companies. This implies that global competition has influenced integrated companies' corporate management and caused differences in efficiency to widen.

Table 5.4 Unified Efficiency under Managerial disposability (UEM)

Company name \ Year	2011	2012	2013	2014	2015
Independent companies					
Anadarko Petroleum Corporation	1.0000	0.7340	0.7697	0.6956	0.6676
Antero Resources LLC	1.0000	1.0000	0.5842	1.0000	1.0000
Apache Corporation	0.5884	0.7356	0.5694	0.7244	0.5718
BHP Billiton Group	0.5737	1.0000	0.5756	0.6981	0.6280
Cabot Oil & Gas Corporation	0.4259	0.4080	0.4810	0.5097	0.4980
Chesapeake Energy Corporation	0.3844	1.0000	1.0000	0.6131	0.5602
Cimarex Energy Co.	0.4225	0.4181	0.4477	0.4906	0.4648
Conoco Phillips	0.4964	0.4946	0.5019	0.5950	0.5638
Continental Resources, Inc.	0.3149	0.4632	0.5997	0.5583	0.5057
Denbury Resources Inc.	0.3481	0.4296	1.0000	0.4853	0.4754
Devon Energy Corporation	0.4659	0.5887	0.5176	1.0000	0.6105
EnCana Corporation	0.4999	0.4596	0.5095	1.0000	0.5409
Energen Corporation	0.4814	0.4486	0.5228	0.5145	0.5181
EOG Resources, Inc.	0.3783	0.5674	0.5856	0.6068	0.6010
EQT Corporation	0.3729	0.4249	0.5239	0.5463	0.5458
Newfield Exploration Company	0.4266	0.4371	0.4851	0.5179	0.5049
Noble Energy, Inc.	0.5359	0.4802	0.5258	0.5755	1.0000
Occidental Petroleum Corporation	0.6207	1.0000	0.6923	0.6704	0.6105
PDC Energy, Inc.	0.4538	0.4079	1.0000	0.5945	0.5495
Pioneer Natural Resources Company	0.4894	0.5942	0.5306	0.5837	0.5426
QEP Resources, Inc.	0.4379	0.4374	0.4111	0.5213	0.4921

Range Resources Corporation	0.4731	0.4487	0.5530	0.5399	0.5098
SM Energy Company	0.4297	0.4193	0.4646	0.5231	0.5003
Southwestern Energy Company	0.4624	0.4458	0.5407	1.0000	0.6285
Ultra Petroleum Corporation	0.4502	0.4154	0.7508	0.5244	0.4979
Whiting Petroleum Corporation	0.4232	0.4350	0.4998	0.6214	0.4805
WPX Energy, Inc.	0.4961	0.4292	0.4444	0.4844	1.0000
Avg.	0.4982	0.5601	0.5958	0.6368	0.5951
Max.	1.0000	1.0000	1.0000	1.0000	1.0000
Min.	0.3149	0.4079	0.4111	0.4844	0.4648
S.D.	0.1576	0.2028	0.1647	0.1645	0.1521
Integrated companies					
BP PLC	1.0000	0.8341	0.8481	0.8478	0.8372
Chevron Corporation	1.0000	1.0000	1.0000	1.0000	1.0000
Exxon Mobil Corporation	1.0000	1.0000	1.0000	1.0000	1.0000
Hess Corporation	0.4684	0.4679	0.4195	0.5125	0.4933
Marathon Oil Corporation	0.4466	0.4563	0.4534	0.5389	0.4970
Murphy Oil Corporation	0.4645	0.4299	0.4026	0.5025	0.5071
Royal Dutch Shell plc	1.0000	1.0000	1.0000	1.0000	1.0000
Avg.	0.7685	0.7412	0.7320	0.7717	0.7621
Max.	1.0000	1.0000	1.0000	1.0000	1.0000
Min.	0.4466	0.4299	0.4026	0.5025	0.4933
S.D.	0.2674	0.2570	0.2706	0.2255	0.2339

(a) Max., Min. and S.D. stands for Maximum, Minimum and Standard Deviation.

(b) Source: Atris and Goto (2019)

Table 5.4 describes the UEM results during the examination period from 2011 to 2015. The worst performer among independent companies was Continental

Resources, Inc. (0.3149 in 2011), while Murphy Oil Corporation was the least efficient among the integrated companies (0.4026 in 2013). These companies display low efficiency scores for all five years. In contrast, three companies–all of them are integrated (Chevron Corporation, Exxon Mobil Corporation, and Royal Dutch Shell Plc) have full efficiency (a score of unity) for all five years. It is interesting to note that Exxon Mobil Corporation's operational efficiency is low, but its environmental efficiency is among the highest. This implies that the company makes efforts to advance in environment protection; however, its environment policy may not be well balanced with its operational efficiency.

Based on average efficiency scores during the examination period, integrated companies constantly outperformed independent companies for all five years. The standard deviations are larger for integrated companies than independent ones. Integrated companies' higher UEM performance can be attributed to different operational characteristics, such as supply chain and operational size, relative to the independent companies. Integrated companies operate not only the upstream but also the downstream business globally. They have direct access to local consumers because they supply O&G to them through their retail branches. These retail businesses effectively enhance the companies' image because consumers and investors prefer to purchase products and invest in companies with a green environmental footprint. Therefore, to maintain their global business reputations, integrated O&G companies should place higher priority on environmental efficiency compared to independent companies, which only operate in the US.

These results are partially consistent with those of Sueyoshi and Wang (2014). In a precise sense, this chapter and their study cannot be directly compared due to different sample companies and examination periods. However, the two studies have significant overlap in the sample of companies and periods: (1) the sample companies for this chapter comprise a subsample of their study, and (2) our five-year study period has one overlapping year (2012). Thus, I believe the comparison is useful in order to understand the implications of these two studies. Their study indicated that integrated companies outperformed independent companies in 2012, including UEN and UEM. This chapter finds the same conclusion for the UEM of the independent and integrated groups in 2012, however, the independent companies outperformed the integrated companies for UEN for that same year. Therefore, the results of this chapter are different from Sueyoshi and Wang (2014) for UEN. As a result, this chapter does not necessarily support the intuitive expectation that larger companies are more operationally efficient than smaller ones.

The different results for UEN between this chapter and the study of Sueyoshi and Wang (2014) may occur due to differences in the examination period and the number of companies (the time period is expanded but the number of companies is slightly reduced for this chapter). In addition, Sueyoshi and Wang (2014) used inputs comprising of (a) acquisition, finding and development (AFD) expenses, (b) R&D expenses, (c) capital expenditures, (d) total assets, (e) number of employees, and (f) number of net wells drilled. On the other hand, this chapter uses: (c) capital expenditures that are classified into two groups–"proved, and unproved properties," and "exploration, development, and others," (d) total assets, (e) number of employees, and (f) number of net wells drilled as inputs. The main reason for these differences in input data is availability, particularly for a balanced five-year panel data set. Furthermore, it is known that AFD expenses are an important factor to assess the performance and future profitability of O&G companies, but there is a discussion on how to calculate the AFD cost for a company. Moreover, R&D expenses are also an important factor to assess research productivity and future innovation, but it is usually difficult to obtain correct and consistent R&D data for each company.

Thus, this chapter only uses data from (c) to (f) as inputs. Such differences in input definitions may influence the efficiency results.

Further, Wang and Li (2018) covered the same period (2011-2015) and used similar methodologies of DEA with this chapter, but this chapter summarizes two differences between their study and this empirical study as follows.

(1) Wang and Li (2018) investigated the carbon emission performance for 31 O&G producers focusing on the upstream segment (independent companies) in the US, using DEA for environmental assessment combined with Malmquist index measurement. They measured the change of carbon emissions performance over time by decomposing it into efficiency change and technological change. Meanwhile, this chapter examines the efficiency of two types of O&G producers, not only independent (upstream) but also integrated (upstream and downstream) companies in the US to compare their performances considering their carbon emission footprints. Using the

DEA environmental assessment combined with KW rank sum test as a statistical interference, this chapter examined whether two types of unified efficiency measures change over time, and whether they differ between the independent and integrated groups of O&G companies. The application of the KW rank sum test is effective because DEA does not incorporate statistical inference in its mathematical structure[46].

(2) Production factors are different in both studies. For instance, Wang and Li (2018) used a data set comprising three inputs (total assets, operational expense, and wells drilled) and four outputs, in which three were desirable (revenue, oil production, and gas production) and one was undesirable (carbon emission). On the other hand, this chapter used five inputs (number of employees; proved and unproved properties; costs for exploration, development, and others; total assets; and number of net wells drilled), and two outputs, one of which is desirable (operational revenue) and the other is undesirable (CO_2 emissions). In addition, Wang and Li (2018) used carbon emission data from onshore and offshore production, but this chapter focused on the onshore production only.

Table 5.5 UEN Rank Sum Test

	df	H statistics	Critical value	P value
Test1	4	6.478	9.488	0.1662
Test 2	1	0.360	3.841	0.5484

Source: Atris and Goto (2019)

[46] There are studies that utilized the DEA model combined with a bootstrapping approach as a statistical inference. See, e.g., Tsolas (2011) to assess the performance of mining operations in the US strip coal mines. Bootstrap DEA is proposed by Simar and Wilson (1998, 2000) that equips DEA with statistical inference using a sampling technique. This chapter does not use such applications. Instead, this chapter is positioned as an early application of DEA environmental assessment to the US O&G companies over multiple periods in recent years in a combination with KW rank sum test.

Table 5.5 presents results for the KW rank sum test for UEN. Test 1 examines the null hypothesis (H_0) that UEN (or UEM in Table 6 below) was uniformly distributed over the five years analyzed in this chapter. Meanwhile, Test 2 examines the null hypothesis that UEN (or UEM in Table 6) was uniformly distributed between independent and integrated O&G companies. The statistics for these two tests (H statistics) are 6.478 for Test 1 and 0.360 for Test 2, with 4 and 1 degrees of freedom (df), respectively. The critical values for the statistics at the 5% level of the significance are 9.488 and 3.841, respectively. Therefore, the null hypotheses (H_0) are not rejected for the two tests. In other words, UEN was uniformly distributed over the five years from 2011 to 2015 (no difference among the five years), and between the two groups of independent and integrated companies (no difference between the two groups).

Table 5.6 UEM Rank Sum Test

	df	H statistics	Critical value	P value
Test1	4	22.226	9.488	0.0002
Test 2	1	7.762	3.841	0.0053

Source: Atris and Goto (2019)

Table 5.6 presents results of the KW rank sum test for UEM. The statistics for these two tests are 22.226 for Test 1 and7.762 for Test 2, with 4 and 1 degrees of freedom, respectively. The null hypotheses are rejected for both tests. In other words, UEM did not uniformly distribute over the five years from 2011 to 2015 (efficiencies differed across the five years), and between the independent and integrated companies (efficiencies differed between the two groups). Therefore, it is statistically confirmed that integrated companies outperform independent companies in environmental efficiency, although there is no statistically significant difference between them in operational efficiency. In addition, the average environmental efficiency has improved in the 2011-2015 period, particularly for independent companies.

5.7 Summary of Chapter 5

This chapter investigated two unified efficiency measures for 34 US O&G companies from 2011 to 2015. The data set includes seven major O&G firms that operate in the US and globally (integrated firms), and companies that operate only in the US (independent companies). The integrated companies operate along the entire supply chain, from upstream exploration to downstream retailing. The independent ones only engage in upstream activities, such as exploration and development. This chapter utilized non-radial DEA models to examine unified efficiency measures for operational and environmental efficiencies. The KW rank sum test was applied to the efficiency measures to test whether the two types of unified efficiency measures have changed over time, and if they differed between independent and integrated O&G companies.

One of the two efficiency measures is UEN that prioritizes operational efficiency over environmental efficiency, while the other measure, UEM, prioritizes environmental efficiency over operational efficiency. The results of UEN indicated that on average independent companies outperformed integrated companies in three out of the five years. This implies that we cannot discuss efficiency issues only in terms of company size and scale economy. However, these differences were not statistically significant. Besides, the efficiency scores were invariant over the five years between 2011-2015.

On the other hand, the results from UEM revealed that integrated companies constantly outperformed independent companies during the study period and UEM varied over time. In other words, the two hypotheses in this chapter were accepted for UEM. The reason for that is large-scale integrated companies operate around the world, so that they are conscious of their environmental footprint in order to meet global standards and measures for environmental protection. Indeed, they are conscious of risk and crisis management, and this helps them obtain access to resources from investors. Further, they differ from independent companies due to their supply chain stretching down to retail consumers. Through that function, corporate managers become conscious of their branding and strive to improve the company's corporate image to promote sales. As a result, integrated companies show higher environmental efficiency than independent companies.

A one limitation of this chapter is its small sample size due to data availability issues. Expanding the sample size to foreign, not just US, firms can help test the influence of corporate scale and supply chain on environmental efficiency. Further, given the increasing importance of new O&G market players who operate in the shale oil/gas business, it would be interesting to examine their efficiency as well.

Chapter 6

Assessment of Oil Refinery Performance: Application of Data Envelopment Analysis-Discriminant Analysis

In chapter 5, the O&G upstream segment is examined focusing only on the US companies (independent and integrated) by DEA using environmental models. Chapter 5 is an extension of the study by Sueyoshi and Wang (2014); therefore, to compare with their study, chapter 5 focuses on the US O&G upstream segment. Besides, the US has a unique feature where all companies (independent and integrated) are private ownership so that the operational data could be obtained from the government website. The US has strict and high standards of environmental regulations that differ from any other country. Further, both are working in the same business segment (upstream), and the technology used in the upstream process is almost the same (e.g., horizontal drilling and hydraulic fracturing). Moreover, both types of companies follow the same environmental regulations. Thus, they are comparable.

In the chapter 6, the O&G downstream segment represented by the refineries is different from the upstream sector. Not all nations have the upstream segment but have downstream segments; therefore, the refineries' sample is expanded to cover four global regions. That supported the study's purpose to give a broad industry evaluation for the downstream segment using a combination of DEA and DEA-DA models. The research motivation for both chapters is related. The main point of chapter 5 is to investigate the importance of vertical integration and supply chain management's impact on the O&G companies (upstream segment) performance.

Further, in this chapter, the main point is to examine the downstream segment in the O&G industry represented by the global refineries. Both chapters are related because they explain how O&G supply chain work and how vertical integration through the supply chain could affect the industry in all stages from upstream to downstream. Besides, in chapter 5, the sample was limited due to research purposes and limited countries that have upstream segment and restricted environmental regulation like the US. However, in chapter 6, all countries have refineries, and there was an opportunity to expand the sample to cover four global regions and give deep insights into the O&G downstream.

6.1 Introduction

Recently, the refineries products' market has witnessed a significant transformation due to the change in products to meet market demand and environmental regulations. Although the refining market is matured and globally widespread, the refineries in developed countries have significantly dropped in their profit margins in the past few years due to a high price of refined oil products. The decrease in the refineries profit margins has been mainly driven by the increase of the prices of the raw materials (e.g., crude oil prices and the proposed local taxes from the governments), which has raised the total cost of final refined oil products. Accordingly, corporate leaders of refineries face pressures that lead to future divestitures of the business. On the other hand, the developing countries have witnessed increases in oil consumption. As a result, the refineries in Asia, the Middle East, and Eastern Europe have significantly upgraded facilities and expanded their scale during the past decade[47].

The O&G refineries have to consider their configuration process to adapt the global market changes. The refinery configuration is the combination of refinery process units that used to produce the final refined products. While the more process units a refinery has the more refinery complexity, therefore, the refinery type defines the refinery complexity level. There are four types of the refineries: topping, hydro skimming, conversion or cracking, and deep conversion or coking refineries. Topping refineries are the simplest type; they work only on crude distillation and basic operation processes. Hydro-skimming refineries include crude distillation process units and more advanced units, such as those for catalytic reforming, hydro treating, and product blending, which upgrade naphtha to gasoline and control the sulfur amount. Cracking refineries include not only hydro-skimming characteristics but also catalytic cracking and hydrocracking processes, so that they can convert the heavy crude oil fraction to lighter products (e.g., gasoline, petrochemical, jet and diesel fuel). Coking refineries are the most complex type. They can convert the heaviest oil residuals to lighter streams and valuable products. Cracking and coking refineries are required to meet the market demand for qualified light products. Refinery complexity

[47] See (http://omrpublic.iea.org/currentissues/full.pdf; BP Statistical Review of World Energy 2011)

depends on several factors, including product demand, local economics and regulations, and crude oil composition (e.g., heavy/light, sour/sweet). All of these factors must be considered in order to enhance efficiency and meet rapidly changing regional and global market trends. The key goal is to gain higher market share and achieve a higher level of profitability in order to maintain competitiveness in the market. Therefore, the regional comparison is essential to illustrate the impact of regional characteristics such as regional location, different patterns of demand in each region, capacity, and resource proximity on the refineries performance. Further, the cost of crude oil to refineries differs across regions based on types of crude oil available to refineries and transportation bottlenecks in each region, and current structure of the refinery industry, and the operational efficiency of the refinery company[48]. Besides, those characteristics determine the refineries profitability (Bandyopadhyay et al. (2019), Cerdá et al. (2018), Zhao et al. (2017), Korotin et al. (2017), Zhang et al. (2001)).

Further, global market regulations and standards impact all refineries' business, which requires environmental performance for refinery operations and major refined products. Thus, refineries should take the global perspective into their accounts to face the global market challenges.

One global environmental protection factor is that the International Maritime Organization (IMO), launched in October 2016, became effective in January 2020. This initiative aims to reduce the amount of sulfur emissions in bunker fuel from its current 3.5% to a maximum of 0.5%.[49] Hence, refineries have to produce a low-sulfur product in order to meet the environmental regulation. The downstream oil market has to adapt to this regulation, and also become more flexible in the face of global challenges by enhancing refineries' ability to meet the global market requirements imposed by falling oil prices (an uncontrollable factor), new regulations on sulfur in marine bunker fuel, and other factors such as regional expansion (e.g., the Asia-Pacific region and the Middle East).

[48] See: THAILAND INDUSTRY OUTLOOK 2018-20, Refinery Industry. (https://www.krungsri.com/bank/getmedia/ab98f86c-6415-4f61-97c7-12126ba58c65/IO_Refinery_2018_EN.aspx).
[49] See (http://www.seatrade-maritime.com/images/PDFs/SOMWME-whitepaper_Sulphur-p2.pdf).

Refinery market capacity varies across regions. Figure 6.1 shows the capacity trends in the four regions examined in this chapter, showing that the Asia-Pacific region has the highest capacity, followed by the US and Canada, Europe, and the Middle East and Africa. Asia Pacific and the Middle East and Africa have seen increasing trends over the last 10 years. On the other hand, the capacity of refineries in Europe has decreased since 2012, while capacity in the US and Canada region is relatively stable, with only a slight increase since 2015.

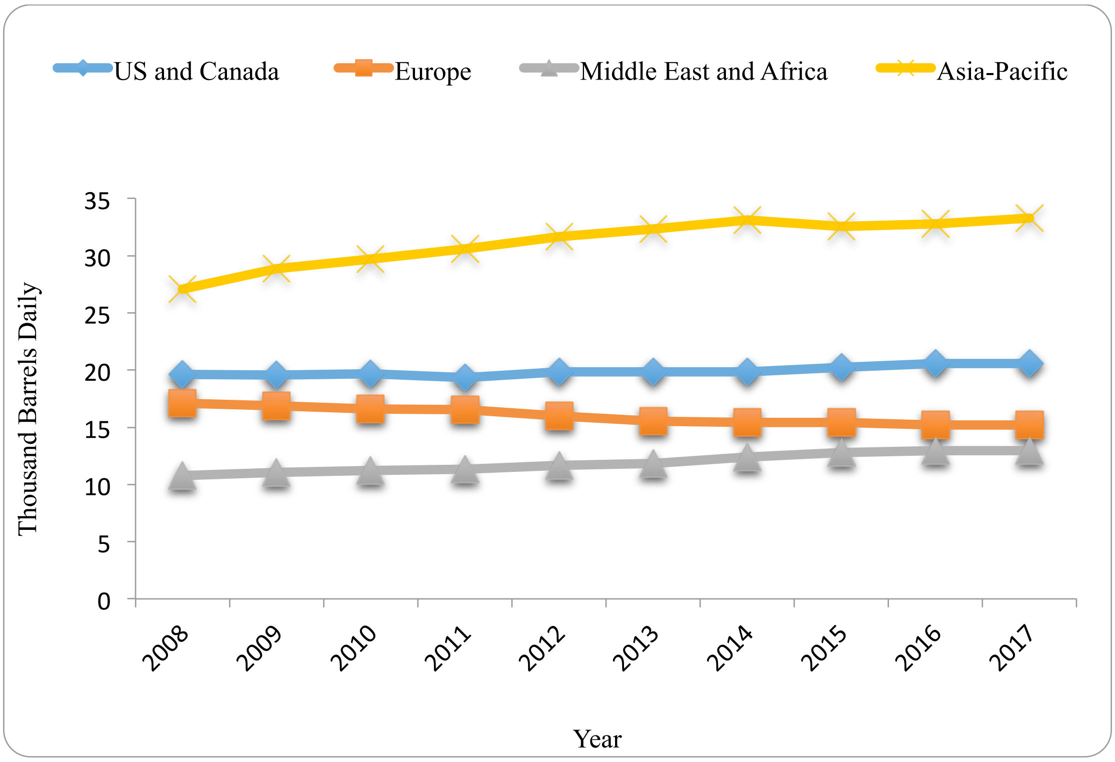

Figure 6.1: Refining Capacity of the Four Regions

Data source: BP Statistical Review of World Energy 2018 (https://www.bp.com/content/dam/bp/business-sites/en/global/corporate/pdfs/energy-economics/statistical-review/bp-stats-review-2018-full-report.pdf).

These regional capacity trends are consistent with future market expectations according to which Asia is expected to lead, with a capital expenditure (capex) of US$254 billion allocated for announced and planned projects up to 2022; this is followed by Africa and the Middle East, with US$117 billion and US$88 billion, respectively.[50] On the other hand, Western Europe has seen many refinery shutdowns, and a maximum of 800,000 barrels/day is at risk of shutdown because of significant challenges caused by changes in crude oil prices, decreasing demand for refineries'

[50] See (https://www.hydrocarbons-technology.com/comment/china-nigeria-drive-global-refinery-capacity-additions-capex/).

products, and environmental regulations.[51] These regional factors are affecting refinery capacity.

The purpose of this chapter[52] is to investigate O&G refineries' operational efficiency in four global regions (US and Canada, Europe, the Asia-Pacific, and Africa and the Middle East) using an unbalanced panel data set comprised of 696 global O&G refineries between 2008 and 2017, and discuss policy implications for the refineries industry operations in every region by obtaining empirically efficiency based rank measures.

This chapter uses a combination of DEA and DEA-discriminant analysis (DEA-DA). DEA classifies refineries into two categories (efficient and inefficient) based on their efficiency scores. Then, DEA-DA is utilized to evaluate all refineries' operational efficiency scores and ranks to get an adjusted efficiency score for each refinery. DEA-DA reduces the number of efficient refineries and generates a single efficient DMU to present a wild industry assessment based upon the efficiencies ranks. Further, due to a lack of statistical inference methods used to complement DEA and DEA-DA computations, a Kruskal–Wallis rank-sum test is conducted to examine whether the average adjusted efficiency-based ranks measures change over time and whether they differ among the four regions. Moreover, a Wilcoxon rank-sum test is utilized to investigate whether the adjusted efficiency averages differ between any two of the regions under study over the ten years between 2008 and 2017. Combining these methods aids the decision making of corporate leaders and policymakers because it allows them to compare operational performance among regional refineries in terms of their efficiency level and of their overall ranking. Corporate leaders tend to pay more attention to their firms' ranking in their industry sector than to their comparative level of efficiency. Efficiency measures and rankings reveal the position of a refinery within the industry and indicate which refineries have room for performance improvement. As mentioned, our performance assessment examines differences across four regions: the US and Canada, Europe, the Asia-Pacific, and Africa and the Middle East.

[51] See (https://www.spglobal.com/platts/en/market-insights/latest-news/oil/091418-more-refineries-at-risk-of-closure-in-europe-new-capacities-elsewhere-platts-summit).
[52] This chapter is based upon the article: Atris, A.M., 2020. Assessment of oil refinery performance: Application of data envelopment analysis-discriminant analysis. Resource Policy. 65 (101543).

The remainder of this chapter is organized as follows. Section 6.2 reviews the literature on DEA studies of O&G refineries. Section 6.3 discusses the study's data set, DEA and DEA-DA formulations, and rank sum tests (KW and Wilcoxon). Section 6.4 discusses the study's empirical results on the refineries' efficiency and rankings based on our regional classification. Section 6.5 presents this chapter's summary and outlines potential future research possibilities.

6.2 Literature Review

6.2.1 Selective DEA Studies Applied to O&G Refineries

After careful review some DEA studies on O&G companies, particularly studies on O&G refineries are found. Further, those studies are limited compared with DEA studies for other applications, despite the importance of refineries' products and their massive economic impact in the petroleum and petrochemical industry. The next table 6.1 summarizes selective DEA studies that applied on O&G refineries, including the authors' names; the studies' methodology, inputs, and outputs used for efficiency assessment; and a brief description of each study.

Table 6.1: Selective DEA Studies Applied to O&G Refineries[53]

Authors	Methodology	Description	Inputs	Outputs
Azadeh et al. (2017)	- DEA -Statistical methods (Spearman's test & alpha test)	This study measured the mutual impact of RE and managerial and organizational factors for 41-gas refineries in Iran.	-Commitment management -Learning -Awareness -Flexibility -Self-organization - Redundancy	-Managerial factors -Organizational factors

[53] This table is updated based upon table (1) in Atris (2020)

Azadeh et al. (2015)	- DEA -Principal Component Analysis (PCA) -Numerical Taxonomy (NTX) -Artificial Neural Network (ANN) -Statistical methods (T-test)	This study presented a combined approach for evaluating the performance of 5 gas refineries in Iran over the period 2005-2009.	-Number of personnel -Total costs (except the cost of goods sold (COGS)) -Personnel education cost -R&D cost -Fixed non-current assets - Stock turnover -Asset turnover ratio -Current assets turnover ratio -Amount of refinery' s fuel consumption/ amount of received sour or sweet gas	-Return on sales -Operating earnings - Net income -Return on assets -Capital return -The amount of gas sent to the torch/ the amount of received sour or sweet gas -Operating capacity divided by nominal capacity -Operating capacity of each LPG production unit divided by design capacity of each LPG production -Operating capacity of each refrigeration and dew point control unit divided by design capacity of each refrigeration and dew point control unit -Operating capacity of each sulphur production unit divided by design capacity of each sulphur production unit -Operating capacity of each liquids stabilization unit divided by design capacity of each liquids stabilization unit -Operating capacity of each dehydration unit divided by design capacity of each dehydration unit.

Bevilacqua and Braglia. (2002)	DEA	This study examined the environmental performance of the seven AgipPetroli oil refineries setup in Italy from 1993 to1996	-Power planet fuel consumption -Oil processed -Refining planet fuel consumption	$-SO_2$ $-NO_x$ -Total Suspended Particles (TSP) -Volatile Organic Compounds (VOC) -CO $-CO_2$
Francisco et al. (2012)	DEA	This study assessed the environmental efficiency for 10 oil refineries in the public sector in Brazil in 2004	-Idleness percentage of the operating plant -The amount of water consumed	-Desirable: (refinery production volume) -Undesirable:(generated effluents)
Li et al. (2017)	DEA	This study examined the sustainable performance for 15 refineries in China	-Asset-liability ratio -Comprehensive energy consumption per unit of output -Entire cost per unit -Solid waste emissions per unit of output -Wastewater emissions per unit of output -Waste gas emissions per unit of output - Employee turnover rate	- Return on assets - Asset turnover -Investment intensity in science and technology - R&A personnel -Comprehensive commodity rate -Environmental protection cost per 10 thousand Yuan of output “three wastes” 1-disposal rates 2-social contribution rate 3-income per capital.

SONG and ZHANG. (2009)	DEA Support Vector Machine (SVM)	This study presented a method for evaluating and predicting oil refineries performance, using two different techniques.	-Manpower cost index -Operation cost index	-Return on average capital employed -Operation cost added value index -Manpower cost added value index -Assets added value index
Al-Najjar and Al-Jaybajy (2012)	DEA	This study measured the relative efficiency of 12 oil refineries in Iraq over the period 2009-2010. The study revealed that there is a waste or underutilization of resources at the inefficient refineries.	- Crude oil - Workforce - Electricity - Land	- Naphtha - Gasoline - Kerosene - Fuel oil
Mekaroonreung and Johnson (2010)	DEA- variable returns to scale (VRS)	This study Investigated the technical efficiency of 113 US oil refineries in operation over two years, 2006 - 2007. They found that domestic refineries could improve efficiencies regardless of the different DEA assumptions. Further, environmental regulations reduced the amount of potentially desirable outputs produced by some facilities.	-Equivalent distillation as a proxy of capital -Energy -Crude oil	- Gasoline -Distillate -Toxic release
Sueyoshi (2000)	A stochastic DEA	This study suggested the DEA approach for planning the restructuring strategy of a Japanese petroleum company in 1998-1999. The results showed that large gas stations operated more efficiently than small ones.	-Number of employees -Size of gas station -Operation cost	-Gasoline -Petrol

Azadeh *et al.* (2017) evaluated the reciprocal impacts of managerial and organizational factors and RE for 41 gas refineries in Iran using DEA and statistical methods. The DEA results indicated that two RE factors (learning and flexibility) had the most influence on the managerial and organizational factors and that the managerial factors had a weaker influence on RE than the organizational factors had. The results of the statistical methods showed that the data were reliable and revealed a strong direct relationship between the two main factors (organizational and managerial). Azadeh *et al.* (2015) applied a combined ANN and multivariate approach to evaluate the performance of five gas refineries in Iran from 2005 to 2009 by considering two cases (financial indicators and financial/non-financial indicators). The refineries were ranked using DEA, PCA, ANN, and NTX. A sensitivity analysis found that the DEA was the most noise-resistant of the methods and that the results for the financial indicators and those for the combined operational indicators differed slightly. Bevilacqua and Braglia (2002) evaluated the environmental efficiency of seven AgipPetroli oil refineries owned by Italy's Eni Group Company. In particular, they examined the environmental impact of their air emissions from 1993 to 1996. They confirmed that an application of an environmental management system (EMS) could generate various benefits, such as reduced liability, improved public image, better compliance, reduced costs, and better access to capital. Francisco *et al.* (2012) used DEA models to evaluate environmental efficiency on the basis of an undesirable output associated with production processes. They found that results obtained without using undesirable output as a basis could be misleading and that environmental regulations seemed to be less effective for efficient refineries. The study also showed the refinery age, as an uncontrollable variable, had no significant effect on the environmental efficiency of the refinery. Sueyoshi (2000) proposed a stochastic DEA model that included future information, called a "DEA future analysis." The suggested approach was used to plan the restructuring strategy of a Japanese petroleum company. The results indicated that large gas stations worked more efficiently than small ones.

Li *et al*. (2017) established a sustainability evaluation index system for refinery firms comprising 17 representative indexes for refineries' sustainability development. They applied a DEA-based model to a sustainability assessment of 15 refineries in China. They provided recommendations for enhancing the refineries' sustainability based on the results, such as reducing the total cost per unit, enhancing investments in science and technology to maintain continuing innovation, increasing the social contribution rate and employee benefits, and considering energy-conservation and emissions-reduction policies in order to achieve clean production. Song and Zhang (2009) presented a novel method of evaluating and predicting oil refineries' performance based on DEA and SVM models. They found that SVM could be used to predict whether an oil refining enterprise was DEA-efficient because the SVM's prediction result was identical to that of the DEA model. Al-Najjar and Al-Jaybajy

(2012) utilized DEA to examine the relative efficiency of a sample of oil refineries in Iraq from 2009 to 2010. They proposed using their research on oil refineries in Iraq in order to determine how best to apply DEA to measure efficiency and overcome efficiency problems. Mekaroonreung and Johnson (2010) measured the technical efficiency of 113 U.S. oil refineries in 2006 and 2007 by comparing multiple DEA methods. They considered undesirable output in the production process and found that domestic refineries could improve efficiencies regardless of the DEA assumptions used and that environmental regulations reduced the amount of potentially desirable outputs produced by some facilities.

Moreover, the O&G industry is a part of the mining, quarrying and O&G extraction sector, where crude oil extraction is considered as liquid minerals. Therefore, it is worthy of mentioning the other applications of DEA on mining and quarrying industries. For example, Zhu *et al*. (2018) utilized slacks-based global DEA to analyze the GTFP of mining and quarrying industry and its five sub-industries in China from 1991 to 2014 concerning technology, scale, and management. Further, they employed a Malmquist index to distinguish the key factors that account for the changes of GTFP. The results indicated that the GTFP of the mining and quarrying industry improved during the period of study due to technological progress, whereas declining in scale efficiency and management efficiency curb the growth of GTFP. Li *et al*. (2019) used a modified dynamic DEA SBM model to estimate the coal production efficiencies and land damage in 24 Chinese provinces from 2011 to 2016. They found that seven provinces were fully efficient in all the study's years, efficiencies of the coal industry labor force, fixed assets, and coal production dropped significantly. However, the land damage was unclear, and Beijing and Guangxi had the least mining quantities, but the greatest need for land damage improvements. Roman *et al*. (2017) applied two-step DEA to evaluate the efficiency of the mining and quarrying industry of Visegrad 4 countries between 2011 and 2015. The results revealed that the Slovak Republic is the most inefficient country. In addition, they employed the double bootstrapped efficiencies that reduce the lack of DEA, and then truncated regression. The results of the proposed model show that Gross investments in machinery, equipment, construction and alteration of buildings and Human Development Index (HDI) have a positive impact on efficiency. Wang and Zang (2018) investigated four key conceptual dimensions of innovation for relative technological innovation of China's coal mine and developed groups of indicators to assess the performance of coal mine's technological innovation activities. Then, they developed an index system based on DEA to audit the progress of innovation and development. They found that the proposed index system and model could effectively assess coal mine's relative technological innovation capability and get the input gap towards efficiency, safety, and sustainability. Hosseinzadeh *et al.* (2016) applied bootstrap DEA to distinguish the balance of efficiency gains and losses for 33 Australian mining firms from 2008 to 2014. The results indicated that mining companies involved in exploration and extraction activities have been less efficient than those involved in metal processing or mining services.

6.2.2 Contribution to the literature

A careful review of DEA studies on O&G refineries revealed that, to the best of my knowledge, this is the first application of a combination of DEA and DEA-DA to O&G refineries. Furthermore, this chapter examines more firms than have been examined in previous studies; the larger dataset allows a broader analysis. To address the shortcomings of previous O&G studies, this chapter uses a unique unbalanced panel dataset for O&G refineries in the four regions listed above covering the 10 years from 2008 to 2017. Further, this chapter reflects the impact of global market challenges and the requirement on refinery efficiency. Then, this chapter addressed some practical suggestions to improve the overall refinery operational efficiency, which have gained importance in modern society as one of the primary energy efficiency issues.

Moreover, this chapter investigates differences in the adjusted efficiency-based ranks among four regions by the KW rank sum test, in which the null hypothesis is that there are no differences in the average adjusted efficiency levels among the four regions or between different periods. As the mathematical structure of DEA applications lack statistical inferences, the KW rank sum test is required to investigate the null hypothesis where different groups or periods have the same distribution for average adjusted efficiency levels.[54] This chapter also utilizes a Wilcoxon rank sum test to check for differences in average adjusted efficiency levels

[54] Bootstrap DEA is proposed by Simar and Wilson (1998, 2000) as a way to equip DEA with statistical inference using a sample technique. This chapter does not use such an application.

between region pairs, where the null hypothesis is that there is no apparent difference in the average adjusted efficiency levels between any two regions.

6.3 Hypotheses

This chapter proposes three null hypotheses based on the results of the previous studies on O&G refineries discussed above.

The operational efficiency of refineries over the world is determined by various vital factors, such as proximity to oil sources, the intensity of oil product consumption, oil transportation routes, and refinery construction. Furthermore, refineries vary by type and oil-refining technology, which condition the complexity level of a refinery.

A refinery's complexity is reflected in its oil-refining capacity utilization and the technology used by the refinery to obtain highly purified oil products. Differences in complexity levels are driven mainly by the regional and locational characteristics of the refineries. Therefore, based on these refinery characteristics, we propose that there are significant differences in average adjusted efficiency levels among the four regions and between any two regions. Our first hypothesis is thus as follows:

> H_0: The average adjusted efficiency measures are invariantly distributed between the four regions. There is no difference between the averages of their adjusted efficiency levels.

The second hypothesis is as follows:

> H_0: The average adjusted efficiency levels in any two regions are equal. No statistically significant differences are observed between any two regions.

Over the last few decades, international oil refinery regulations have been strengthened in order to reduce pollution. Environmental regulation by the IMO is one of the most significant challenges facing refineries all over the world. The IMO is pressuring refineries to produce low-sulfur products. For instance, refineries in North America and Europe have to reduce their sulfur oxide content to levels under 0.1%. While Asia and the Middle East are witnessing the construction of many complex refineries and anticipating a projected capacity increase of 7 million additional barrels per day by 2023, the IMO is radically changing refineries' processes (complexity) in order to reduce the sulfur content of fuel oil used in ships from 3.5% to a maximum of

0.5%. The IMO's regulations will come into effect in January 2020, which is outside our study period. Therefore, the third null hypothesis is as follows:

H_0: The average adjusted efficiency measures are invariantly distributed over the 10 years of the study period. No statistically significant shifts in average adjusted efficiency levels occur over time.

6.4 Methodology

6.4.1 Data

This chapter applies an unbalanced panel dataset[55] comprising O&G refineries located in the four regions listed above. The dataset was collected using S&P CAPITAL IQ PLATFORM[56] covering 2008 to 2017. This chapter uses two DEA models: the first is the DEA radial model (input oriented), which is used for efficiency assessment; the second is the DEA-DA model, which is used for group classification and ranking via a financial dataset that contains four inputs and three outputs[57]. These are summarized below.

6.4.1.1 [Four Inputs]

- **Number of employees:** This variable reflects one of the main input factors used in the production process, along with capital and materials. This variable is often used as an index for company size and scale. It is the main factor considered in M&A (mergers and acquisitions) decisions because their main target is often to reduce the number of employees and labor costs.
- **Total assets:** This variable reflects the total amount of investment, cash, equipment, receivables, and all other assets as reported in the balance sheet. Moreover, total assets as an input reflects the borrower's fiscal strength. This input consists of two kinds of assets: current and fixed. More total assets

[55] The combination of the data or suitable inputs and outputs is different between the two central chapters (5 and 6) based on the purpose of the study and the dataset's availability. The combination of inputs and outputs is not fixed and depends on each DEA model. Further, the selection of the dataset is a free choice of the researcher. For example, the dataset selection in chapter 5 following the Sueyoshi and Wang (2014) study to compare between their study and chapter 5. However, in chapter 6, the DEA utilized models and purposes are different; therefore, the sample of inputs and outputs is different from chapter 5. Every input represents the main production factors in creating or producing a company's value, and every output represents the value-added or created by the utilized inputs.

[56] See S&P CAPITAL IQ PLATFORM: https://www.spglobal.com/marketintelligence/en/index.

[57] The two inputs (number of employees and total assets) used as a proxy of the company size and there is no duplication between the inputs that utilized in the two central chapters (5&6). Further, The sources of the dataset, company type, and examination periods are also different between the two chapters.

produce more revenue and income. This variable can also be used as a firm size index.

- **Total cash and short-term investments:** This variable reflects a kind of current assets that are highly liquid; these can be used quickly if the company needs quick money or cash. Higher cash and short-term investments allow firms to hedge against unexpected future fluctuations in profits and to enhance their liquidity ratios.
- **Total debt:** This variable reflects the volume of loans and liabilities that the company uses to finance its investments, including long- and short-term liabilities. Higher total debt to total assets increases the degree of leverage and financial risk.

6.4.1.2 [Three outputs]

- **Total revenue:** This reflects the total amount of money that the company receives from the sales of products and services in a specific period. Higher revenue indicates that the company is successful in its business sector.
- **Net income:** This variable indicates the net amount of money (profit) that the company earned in a specific period. This variable is calculated by subtracting all the business expenses from the amount of total revenue. Increased net income indicates a net increase in shareholders' equity, which will be distributed as dividends among the shareholders.
- **Total enterprise value (TEV):** This determines the overall economic value of the company. It is calculated as the market price of a stock multiplied by the total number of shares outstanding. This variable is an important measure for analyzing potential takeover targets.

Table 6.2 Production Factors for the Refineries' Companies among Four Regions

			Outputs			Inputs			
Variable			Net Income	Total Revenue	Total Enterprise Value	Employees	Total Assets	Total Cash & ST Investment	Total Debt
Unit			Millions$	Millions$	Millions$	Employee	Millions$	Millions$	Millions$
2008	Avg.	U.S. and Canada	151.3	10711.2	1625.0	2760.7	2795.4	109.7	747.2
		Europe	59.0	5674.2	1711.0	1472.2	2004.0	123.7	542.2
		Asia- Pacific	418.3	14331.7	5691.9	5417.4	7922.0	603.7	2421.4
		Africa and Middle East	63.5	4705.3	948.1	937.9	1636.5	312.9	466.1
	Total Avg.		267.2	11171.1	3629.9	3728.5	5193.3	399.4	1550.7
2009	Avg.	U.S. and Canada	38.2	2547.7	790.7	879.0	1039.9	59.3	289.6
		Europe	225.5	9074.4	4586.6	6061.3	6417.5	262.7	1959.7
		Asia-Pacific	67.6	7789.0	2391.0	3532.9	3438.1	471.8	1254.8
		Africa and Middle East	102.3	3168.8	990.3	922.5	1549.5	303.6	521.2
	Total Avg.		85.6	5813.5	1983.2	2675.7	2838.7	324.9	966.3
2010	Avg.	U.S. and Canada	76.1	11611.1	2704.9	2796.0	4675.9	469.6	1022.6
		Europe	230.0	10147.0	3789.2	4978.8	5943.8	311.6	1542.8
		Asia-Pacific	161.1	8453.5	3033.1	3332.6	4565.6	438.0	1435.4
		Africa and Middle East	94.9	5218.5	3637.4	1505.3	4068.3	544.7	1673.8
	Total Avg.		141.4	8815.1	3167.3	3138.7	4694.1	445.2	1402.2
2011	Avg.	U.S. and Canada	355.5	16002.6	2553.0	3551.2	5360.8	416.9	964.8
		Europe	153.3	10258.3	2418.7	4132.8	4772.9	265.3	1306.2
		Asia-Pacific	300.2	13587.5	3773.6	3699.6	7453.6	434.8	2492.8
		Africa and Middle East	83.9	4857.8	2151.6	1244.5	2840.5	170.0	1102.4
	Total Avg.		265.6	12551.7	3047.6	3351.9	5897.3	370.9	1739.0
2012	Avg.	U.S. and Canada	638.9	24897.1	5532.8	4240.1	7712.6	791.8	1237.1
		Europe	154.8	13141.4	3114.4	4350.0	5547.0	299.4	1346.9
		Asia-Pacific	166.6	15580.4	4970.4	3884.5	8137.7	438.2	2788.6
		Africa and Middle East	79.9	4841.8	1900.0	980.6	2581.1	223.7	1134.9
	Total Avg.		276.4	15718.6	4310.4	3459.2	6636.8	476.5	1880.3
2013	Avg.	U.S. and Canada	596.5	28504.8	7770.0	4489.2	9004.8	903.9	1314.4
		Europe	152.0	12704.4	3521.2	5865.2	6249.7	327.2	1227.8
		Asia-Pacific	165.5	14239.7	3725.8	3725.8	7027.6	366.5	2320.8
		Africa and Middle East	63.0	3486.2	1234.6	729.4	1720.5	197.6	592.4
	Total Avg.		265.6	16254.1	4407.5	3618.2	6633.0	482.7	1671.1
2014	Avg.	U.S. and Canada	564.1	20873.1	6388.7	4094.1	7427.7	625.8	1488.6
		Europe	30.9	5967.3	2979.6	1879.7	3065.0	117.4	848.2
		Asia-Pacific	108.9	11925.9	3171.5	2931.8	6296.1	495.9	2277.5
		Africa and Middle East	75.6	2720.6	1239.3	1041.8	1361.5	190.9	448.2
	Total Avg.		271.7	13570.7	4067.4	3022.7	5795.3	479.8	1626.5
2015	Avg.	U.S. and Canada	838.1	19835.8	9706.8	6012.2	10721.8	770.2	2307.8
		Europe	252.3	8602.6	3386.8	4412.9	4707.9	592.3	1245.2
		Asia-Pacific	49.1	3452.7	1468.3	1235.5	1620.4	146.5	493.3
		Africa and Middle East	97.5	1784.2	1239.4	885.9	1125.6	126.8	392.5
	Total Avg.		280.5	7891.0	3726.4	2763.7	4192.4	354.6	1022.7
2016	Avg.	U.S. and Canada	379.9	17426.9	10694.0	5916.4	11748.1	900.1	2817.8
		Europe	392.4	7132.1	3433.9	4291.3	4655.8	502.3	1002.7
		Asia-Pacific	71.0	2877.4	1262.9	1262.5	1606.1	161.4	424.3
		Africa and Middle East	78.6	1779.9	1191.1	972.8	1572.0	198.6	553.4
	Total Avg.		182.3	6442.6	3614.0	2630.6	4235.1	375.5	1051.3
2017	Avg.	U.S. and Canada	1026.1	22248.6	14951.9	6611.3	14869.3	997.7	3627.1
		Europe	467.7	9330.4	4646.2	4126.4	5316.7	603.9	911.6
		Asia-Pacific	311.5	8054.9	5993.2	6069.6	7436.7	629.5	2232.6
		Africa and Middle East	116.2	2215.3	1358.8	940.3	1649.4	241.8	587.4
	Total Avg.		435.8	9934.7	6738.3	4986.8	7571.4	627.3	2040.3
Total	Avg.	All	3364.81	439.03	1516.01	5474.22	253.64	10962.30	3960.15
	Min		1.00	0.04	0.00	2.08	0.12	0.38	1.61
	Max		140483	10474	30342	109937	5106	165960	100833
	S.D.		8244.02	917.41	3416.99	11648.72	659.89	22079.99	8916.45

(a) Avg., Max., Min., and S.D. stands for Average, Maximum, Minimum and Standard Deviation.

(b) Source: Atris (2020)

Table 6.2 presents descriptive statistics for the data on refining companies operating in the US and Canada, Europe, the Asia-Pacific, and Africa and the Middle East. The average, standard deviation, minimum, and maximum are denoted by "Avg.," "S.D.," "Min.," and "Max.," respectively. In 2008, the Asia-Pacific region exceeded the other three regions in all average production factors. This is due to the increased demand for refinery products in their markets, particularly China and India. Large-scale upgrading is ongoing as a response to this increase in market demand. From 2014 to 2017, the US and Canada region shows the highest values for all production factors except total debt and net income in 2014 and 2016. Since 2014, US shale oil has created a boom in the crude oil industry in this region and led the US to become a crude oil exporter in 2017 for the first time. Shale oil made up more than 1/3 of the onshore production of crude oil in the US.

The Asia-Pacific region has the highest total debt among all regions in 2008, and from 2011 to 2014, the values were \$2421.4, \$2492.8, \$2788.6, \$2320.8, and \$2277.5 million US, respectively. The U.S. and Canada region shows the highest total revenue from 2010 to 2017, at \$11611.1, \$16002.6, \$24897.1, \$28504.8, \$20873.1, \$19835.8, \$17426.9, and \$22248.6 million US\$, respectively. The input and output datasets show the highest average levels for all regions in 2017, except for total revenue in 2013, which displays the highest value (\$16254.1 million US).

6.4.2 Models

6.4.2.1 DEA

This chapter applies a radial input-oriented DEA model under the assumption of VRS technology. This model reduces inputs to produce a certain amount of outputs and removes the scale economy or diseconomy of a DMU from the efficiency score. This model is often used in empirical studies of DEA.

The mathematical symbols used to illustrate production factors are as follows:

(a) $X_j = \left(x_{1j}, x_{2j}, \dots, x_{mj}\right)^T > 0$: a column vector of m inputs of the *j*-th DMU ($j = 1, \dots, n$), and

(b) $Y_j = \left(y_{1j}, y_{2j}, \dots, y_{sj}\right)^T > 0$: a column vector of s outputs of the *j*-th DMU ($j = 1, \dots, n$), where superscript "T" indicates a vector transpose. The inequality (>) implies that the relationship is applied to all components of the two column vectors.

In addition to the above production factors, which are given as an observed dataset, this chapter uses the following symbols (unknown), which are measured by applying the DEA:

(c) $d_i^x \geq 0$: unknown slack variable of the *i*-th input ($i = 1, \dots, m$),

(d) $d_r^y \geq 0$: unknown slack variable of the *r*-th output ($r = 1, \dots, s$),

(e) $\lambda = (\lambda_1, \dots, \lambda_n)^T$: unknown column vector of "intensity" or "structural" variables,

(f) ε: a small number to be prescribed by the DEA researcher, in this chapter $\varepsilon = 0.0001$.

The input-oriented radial DEA model used in this chapter is as follows:

$$
\begin{aligned}
&Minimize\ \ \theta + \varepsilon\left[\sum_{i=1}^{m} d_i^x + \sum_{r=1}^{s} d_r^y\right] \\
&s.t. \qquad \sum_{j=1}^{n} x_{ij}\lambda_j + d_i^x = \theta x_{ij} \quad (i = 1, \dots, m), \\
&\qquad\quad\ \ \sum_{j=1}^{n} y_{ij}\lambda_j - d_r^y = y_{rj} \quad (r = 1, \dots, s), \qquad (6.1) \\
&\qquad\quad\ \ \sum_{j=1}^{n} \lambda_j = 1, \\
&\qquad\quad\ \ \lambda_j \geq 0\ (j = 1, \dots, n), \theta{:}\ URS, d_i^x \geq 0\ (i = 1, \dots, m), d_r^y \geq 0\ (r = 1, \dots, s),
\end{aligned}
$$

Where URS is unrestricted.

6.4.2.2 DEA-DA

The DEA method is a management science technique, and DA is a statistical methodology. The DEA-DA is a research tool that combines managerial and statistical approaches to predict group membership in sampled data. This chapter applies a DEA-DA model and classifies all DMUs into efficient (E) and inefficient (IE) groups as formulated in Model (6.2):

$$Min. \qquad M\sum_{j\in E} Z_j + \sum_{j\in IE} Z_j$$

$$St. \qquad -\sum_{i=1}^{m} v_i x_{ij} + \sum_{r=1}^{s} w_r y_{rj} + \sigma + Mz_j \geq 0,\ j \in E,$$

$$-\sum_{i=1}^{m} v_i x_{ij} + \sum_{r=1}^{s} w_r y_{rj} + \sigma - Mz_j \leq -\varepsilon,\ \ j \in IE, \qquad (6.2)$$

$$\sum_{i=1}^{m} v_i + \sum_{r=1}^{s} w_r = 1,\ \ v_i \geq\ \varepsilon\zeta_i,\ i = 1,\dots,m,\ \ w_r \geq\ \varepsilon\zeta_r,\ \ r = 1,\dots,s,$$

$$\sum_{i=1}^{m} \zeta_i = m,\ \ \sum_{r=1}^{s} \zeta_r = s, \sigma{:}\ URS,\ v_i\ \geq 0\ for\ all\ i,\ \ w_r\ \geq 0\ for\ all\ r,$$

$$Z_j{:}\ binary\ for\ all\ j,\ \zeta_i{:}\ \ binary\ for\ all\ i,\ \ and\ \zeta_r{:}\ binary\ for\ all\ r.$$

Here, M is a prescribed large number, and ε is a prescribed small number. It is necessary to specify the two numbers before solving Model (6.2). The objective function minimizes the total number of incorrectly classified DMUs by counting a binary variable (Z_j). In this classification, the inefficient group (IE) has less priority than the efficient group (E). Therefore, we add M to the efficient group in the objective of Model (6.2). The discriminant score is expressed by $-\sigma\ (j \in E)$ and $-\sigma - \varepsilon\ (j \in IE)$, respectively. The small number (ε) is incorporated into Model (6.2) in order to avoid a case where an observation exists on an estimated discriminant function.

All the DMUs are classified by a discriminant function $(-\sum_{i=1}^{m} v_i x_{ij} + \sum_{r=1}^{s} w_r y_{rj} + \sigma)$. Unknown weights $(v_i \; for \; i = 1,\ldots,m, \; w_r \; for \; r = 1,\ldots,s)$ indicate the slope of the discriminant function. (Note that v_i and w_r are dual variables (multipliers) in the DEA but are weights in the DEA–DA.) The constraints $(\sum_{i=1}^{m} v_i + \sum_{r=1}^{s} w_r = 1, \; v_i \geq \varepsilon\zeta_i, \; i = 1,\ldots,m, \; w_r \geq \varepsilon\zeta_r, \; r = 1,\ldots,s)$ indicate that all the weights are positive, so that the discriminant function is a full model. The sum of the unknown weights is unity. This restriction is often referred to as "normalization." Model (6.2) incorporates binary variables (ζ_i: binary for all i, andζ_r: binary for all r) to count the number of positive weight estimates. It is possible to change the number of binary variables to set the weights at a number lower than the actual number (i.e., it is possible to reduce the number of binary variables according to the importance of each factor and depending on whether you need to deal with zero and/ or negative data). Such a change depends upon the degree of freedom between the number of observations (DMUs) and the number of weights. After applying Model (6.2) to the dataset, we obtain an optimal solution and compute the following score for the j-th DMU:

$$\rho_j = -\sum_{i=1}^{m} v_i^* x_{ij} + \sum_{r=1}^{s} w_r^* y_{rj} + \sigma^* \qquad for\; all\, j = 1,\ldots,n. \tag{6.3}$$

Using the ρ_j score, the adjusted efficiency score is computed for the refineries through the following procedure:

(a) Find the maximum and minimum values of ρ by $max_j \; \rho_j$ and $min_j \; \rho_j$.

(b) Find the range between them by

(b-1) range (A) = $max_j \; \rho_j - min_j \; \rho_j$ if min_j is non-negative and

(b-2) range (B) = $max_j \; \rho_j + |min_j \,|$ if $min_j \; \rho_j$ is negative.

(c) The adjusted efficiency score for the j-th DMU is measured by

(c-1) Efficiency =$[\rho_j - min_j] \,/\, [range\ (A)]$ if $min_j \; \rho_j$ is non-negative and

(c-2) Efficiency =$[\rho_j + min_j] \,/\, [range\ (B)]$ if $min_j \; \rho_j$ is negative.

6.4.2.3. Rank sum tests

This chapter utilizes the KW rank sum test (H) to examine the null hypotheses regarding whether the different groups and periods have the same distribution. This chapter reorders all DMUs in ascending order based on their average adjusted efficiency scores to compute the test (Sueyoshi and Goto, 2012). Let R_{jt} denote the rank of the j-th DMU in the t-th group (or period). The rank sum of all DMUs in the t-th group (or period) is $R_t = \sum_{j=1}^{n} R_{jt}$ where n stands for the number of companies at the t-th group (or period). The KW test is mathematically expressed as follows:

$$H = \frac{12}{N(N+1)} \sum_{t=1}^{T} \frac{R_t^2}{n} - 3(N+1). \qquad (6.4)$$

Here, the number (N) refers to the total number of DMUs in all groups (or periods). The statistic (H) follows the x^2 distribution with a degree of freedom (df = T-1). Hollander and Wolfe (1999) have described the Kruskal–Wallis rank sum test in detail.

When multiple DMUs have the same rank, the H statistic needs to be adjusted as follows:

$$H^c = \left\{\frac{12}{N(N+1)} \sum_{t=1}^{T} \frac{R_t^2}{n} - 3(N+1)\right\} / \ (1 - \frac{\Sigma \quad q}{N^3 - N}). \qquad (6.5)$$

Here, $q = z^3 - z$ where z denotes the number of observations on the same rank.

6.4.2.4 Wilcoxon rank sum test:

This chapter applies a Wilcoxon rank sum test (also known as the "Mann–Whitney test") to examine the null hypotheses regarding whether there is no significant statistical difference between any two regions (i.e., whether the medians of the two regions are equal; Mann and Whitney, 1947). The rankings of the DMUs are calculated according to their average adjusted efficiency scores. As both samples are larger than 10, the Wilcoxon rank sum test is mathematically treated as follows:

$$\mu_A = \frac{n_A(n_A+n_B+1)}{2} \quad (6.6)$$

$$\sigma_A = \sqrt{\frac{n_A n_B(n_A+n_B+1)}{12}} \quad (6.7)$$

$$z = \frac{R_A-\mu_A}{\sigma_A} \quad (6.8)$$

Here, μ_A is the mean for group A (i.e., the expected value for group A), σ_A is the variance of group A, R_A is the sum of the rankings of group A, and Z is the critical value.

6.5 Empirical Results

Table 6.3 Summarized Efficiency Results of Model (6.1)

Efficiency score	1	0.9	0 .8	0 .7	0 .6	0 .5	less than 0.5	Number of companies
US and Canada	46 (26%)	8 (4%)	14 (8%)	17 (10%)	16 (9%)	16 (9%)	61 (34%)	178
Europe	4 (6%)	1 (2%)	1 (2%)	2 (3%)	7 (11%)	9 (14%)	42 (64%)	66
Asia-Pacific	40 (12%)	11 (3%)	10 (3%)	15 (5%)	26 (8%)	18 (5%)	208 (63%)	328
Africa and Middle East	11 (9%)	4 (3%)	11 (9%)	12 (10%)	13 (10%)	17 (14%)	56 (45%)	124

Source: Atris (2020)

The number of companies and their efficiency results obtained from model 1 are summarized in Table 6.3. The total number of refineries in each region is 178 in the US and Canada, 66 in Europe, 328 in the Asia-Pacific region, and 124 in Africa and the Middle East. These results show that the highest efficiency score is for the US and Canada, where 46 firms achieved an efficiency score of 1, and 61 refineries received scores of less than 0.5; these represent 26% and 34%, respectively, of the US and Canada sample. Europe has the lowest number of firms because of the wave of refinery shutdowns over the last decade Four refineries in Europe are fully efficient, with an efficiency score of 1, and 42 companies have efficiency scores less than 0.5; these firms represent 6% and 64% of the European sample, respectively. The Asia-Pacific region has the highest number of refineries in the sample. Only 40 of the region's refineries are efficient, and 208 obtained efficiency scores less than 0.5; these refineries represent 12% and 63% of the Asia-Pacific sample, respectively. Africa and the Middle East region has 11 efficient refineries and 56 firms with scores less than 0.5; these represent 9% and 45% of the sample, respectively.

Table 6.4 Averages of Efficiency and Adjusted Efficiency Scores

Region		Year	Average of efficiency score	Average of adjusted efficiency	Ranks
US and Canada	Avg.	2008	0.6761	0.5589	21
		2009	0.7069	0.6589	39
		2010	0.5805	0.5825	31
		2011	0.6281	0.6184	35
		2012	0.7087	0.6578	38
		2013	0.7497	0.6661	40
		2014	0.7103	0.6543	37
		2015	0.6694	0.6416	36
		2016	0.5654	0.5310	13
		2017	0.6599	0.6040	34
Europe	Avg.	2008	0.4243	0.6015	33
		2009	0.4650	0.5205	8
		2010	0.4753	0.5612	24
		2011	0.4301	0.5508	17
		2012	0.4447	0.5096	3
		2013	0.4315	0.5100	4

		2014	0.3200	0.5270	10
		2015	0.4376	0.5305	11
		2016	0.4899	0.5413	14
		2017	0.5848	0.5771	28
Asia-Pacific	Avg.	2008	0.5454	0.5583	20
		2009	0.4584	0.5112	5
		2010	0.4815	0.5647	25
		2011	0.4942	0.5600	22
		2012	0.4978	0.5076	2
		2013	0.5123	0.5308	12
		2014	0.3876	0.4874	1
		2015	0.4949	0.5807	29
		2016	0.4581	0.5456	15
		2017	0.5145	0.5689	26
Africa and Middle East	Avg.	2008	0.6263	0.5559	19
		2009	0.6694	0.5820	30
		2010	0.6358	0.5712	27
		2011	0.5393	0.5529	18
		2012	0.6202	0.5859	32
		2013	0.5527	0.5177	6
		2014	0.5823	0.5244	9
		2015	0.5633	0.5610	23
		2016	0.5145	0.5202	7
		2017	0.4870	0.5486	16

Source: Atris (2020)

Table 6.4[58] shows a comparison of average efficiency scores using the conventional DEA and average adjusted efficiency scores using DEA-DA. To clarify the difference, for 2014, the average efficiency scores and average adjusted efficiency scores are 0.3200 and 0.5270 for Europe 0.7103 and 0.6543 for the US and Canada, respectively. The DEA-DA results show that applying this discriminant analysis to an industry-wide evaluation is important for determining the real efficiency performance in each region.

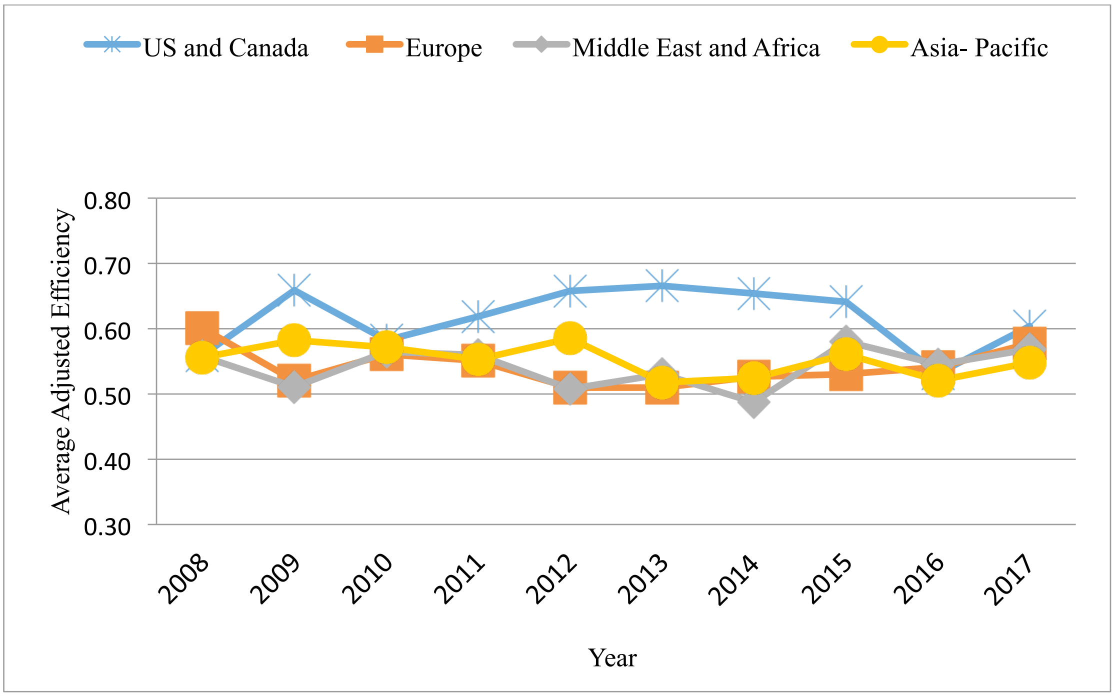

Figure 6.2: Average Adjusted Efficiency Scores of the Four Regions

Source: Atris (2020)

Figure 6.2 depicts the average adjusted efficiency scores of the four regions from 2008 to 2017. The US and Canada region shows the best performance, followed by the Asia-Pacific, Africa and the Middle East, and Europe. The high performance in North America is due to the shale boom, which changed the position of the US in the global oil market, particularly in the petrochemicals industry. Petrochemical companies and gas investors in the US and Canada have invested greatly in refineries

[58] Note: the DEA-DA Model obtains the adjusted efficiency score. This chapter proposed M= 10000 and ε=0.0001for the computation of the DEA-DA model. The optimal solution of DEA-DA is v_1 =0.0001, v_2 =0.1307, v_3=0.1535, v_4 = 0.2287, w_1 = 0.1727, w_2= 0.0174, w_3= 0.2968 and σ = 0.008

and natural gas plants, as well as the extraction and processing of natural gas liquids (e.g., ethane, pentane, propane, butane). Moreover, the low cost of ethane in the US enhances the efficiency of US refineries and gives US producers a competitive advantage.

Further, US refineries exceeded 17mb/d in 2017, with a 92% capacity utilization rate. Most of this capacity comes from the Gulf Coast region, and it is expected to promote US capacity over the next few years. The increase in US crude oil output, along with the inflows of discounted Canadian crude oil, are the main drivers of the change in the US position in the global oil market. The US refineries market has unique conditions; for instance, US refineries are the most complex refineries in the world based on the Nelson Complexity Index (NCI)[59], which considers what kinds of petroleum products a refinery can produce. In 2014, for example, 70% of refineries in the US had the NCI between 6 and 12, 13% of refineries with NCI greater than 12, and 30% of the US refineries have the NCI greater than 10 (Kaiser 2017). The complex refineries gain the advantage of the price differentials that exist between different crude oils due to supply and demand, gravity, quality, and location imbalances. Besides, the US, according to BP Statistical Review of World Energy 2018, has the highest refineries capacity in the world, at 18.61, 18,57, 18.76, and 18.97 Mbpd in 2016, 2017, 2018, and 2019, respectively[60]. The US refineries rely on the leading edge, world-class technologies, e.g., hydraulic fracturing and horizontal drilling. Much of it developed in the US that gives the country a competitive advantage regarding the technology costs. Further, many factors supported the US's dominance, such as a) access to cheap natural gas and low American crude oil price. The discount on US crude oil is partially attributed to the long-standing federal ban until 2017 on US crude oil exports. This ban reduces the total costs and enhances the refineries' performance in terms of minimizing the total coast, maximizing the refinery profits, b) crude pricing at export parity and strong demand for product exports. Further, Thanks to vertical integration that is mainly driven by integrated and majors O&G companies, the US and Canada uneconomical production sites became feasible to use because of the abundance of new technologies

[59] Nelson Complexity Index was developed in 1960 by Wilbur L Nelson to measure the sophistication of a refinery, where more complex refineries are able to produce lighter, more heavily refined, and valuable products. The measuring scale is from 1 to 20, where a low range represents refineries that are simple and produce low-quality fuel, e.g., heating oil, jet fuel, and a high number indicates more complicated and expensive refineries that produce high-quality light fuels, e.g., kerosene and gasoline.

[60] See (https://www.statista.com/statistics/273579/countries-with-the-largest-oil-refinery-capacity/)

developed. For instance, (fracking, deep-water wells, horizontal drilling, perforation, etc.) lead to growing US crude output and increasing inflows of discounted Canadian crude oil. The fracking (hydraulic fracturing) technique has allowed the US to boost and increase domestic oil production and reduced US oil imports, enhancing US refineries' efficiency and profitability. The vertical integration also leads to fewer bottlenecks and an increase in capacity at the larger sites.

The Asia-Pacific region is endeavoring to boost the productivity and efficiency of its O&G refineries and reserves to meet increasing energy demand. China, India, and some parts of Thailand, Indonesia, and Malaysia have mature O&G reserves. Emerging markets such as the Philippines and Myanmar have begun developing new oil fields. The main O&G industry players in the Asia-Pacific region are divided into national oil companies (NOCs) and international oil companies (IOCs). NOCs include the China National Offshore Oil Corporation (CNOOC), India's Oil and Natural Gas Corporation (ONGC), Malaysia's Petronas, Thailand's PTT, and Vietnam's PetroVietnam. NOCs are leading the investment and development of the regional O&G industry. Meanwhile, IOCs such as Exxon Mobil, BP, Chevron, Shell, and Murphy are helping to expand the Asia-Pacific O&G market through many joint ventures. For instance, Papua New Guinea's InterOil was acquired by Exxon Mobil, BP plans to expand its Tangguh LNG project in Indonesia, and Exxon Mobil and Chevron are investing in oil ventures in Kazakhstan to transport crude oil to China. Other IOCs and independents are also participating in O&G market activities, including Reliance (one of India's largest private sector companies), Murphy, and Shell.

Africa and the Middle East region (particularly the Middle East) is increasing its refinery capacity and investing more in technology to integrate its upstream and downstream sectors[61]. Saudi Arabia is a significant oil-producing nation not only in the region but also in the world. It is working on maintaining its capacity and enhancing its refineries' throughput via joint ventures. For instance, Saudi Aramco closed the Jeddah refinery in 2017 to enhance its domestic business. The company is working to expand its downstream business overseas through joint ventures in emerging markets in Asia (e.g., China, Malaysia, and Indonesia); it is also expanding

[61] Sueyoshi and Wang (2014), and Atris and Goto (2019) discussed the role of supply chain and vertical structure in enhancing the overall efficiency in the O&G industry.

in the US by consolidating operations at the Motiva plant (600 kb/d) in a joint venture with Shell. Saudi Aramco currently refines only 30% of its crude oil production; it aims to double its refining capacity and increase its crude productivity. To this end, Saudi Aramco and SABIC petrochemical company signed an agreement to construct a 400 kb/d crude-producing chemical complex by 2025. Other Middle Eastern countries, such as Bahrain, Kuwait, and Oman, are also pursuing overseas expansion. The UEA has been less active in expanding its capacity. However, ADNOC is starting main upgrades to refine sour crude through its Ruwais refinery.

The Middle East is expected to attain the world's highest crude productivity by 2023. Africa has a low average utilization rate, of fewer than 70%. However, it is working to increase its refinery capacity. Nigeria will drive capacity growth in Africa and the Middle East by adding 1.933 md/d by 2022.[62] The worst performance is seen in Europe due to the changes in their market patterns caused by the switchover to electric vehicles and buses and because Europe is moving toward a low-carbon economy and the use of fuel-mix energy.

Refineries' margins and fuel oil production are susceptible to oil price fluctuations, as shown in Figure 6.2. Average adjusted efficiency in all regions increased in 2015 due to declining oil prices in 2014, which affected all refineries' margins and profits due to the increased demand for their products. However, in 2016, all regions recorded a drastic decrease in average adjusted efficiency due to OPEC's decision to cut their oil production to increase oil prices.

Table 6.5 KW Rank Sum Test

	df	H statistics	Critical value	P value
Test 1	3	14.340	7.815	0.002
Test 2	9	6.918	16.919	0.646

Source: Atris (2020)

[62] See: https://www.hydrocarbonengineering.com/refining/03092018/nigeria-will-propel-refining-capacity-growth-in-the-middle-east-and-africa/.

Table 6.5 presents the KW rank sum test results for the average adjusted efficiency scores. Test 1 investigates the null hypothesis (H_0) that the average adjusted efficiency measures are uniformly distributed among the four regions, while test 2 examines the null hypothesis (H_0) that the average adjusted efficiency scores are uniformly distributed over the 10 years analyzed in this chapter. The test statistics (H statistics) are 14.847 for test 1 and 3.902 for test 2, with 3 and 9 degrees of freedom (df) respectively. The critical values for the statistics are 7.815 and 16.919, respectively, at the 5% significance level. The null hypotheses are thus rejected for test 1 but not for test 2. In other words, the average adjusted efficiency did not uniformly distribute among the four regions (the adjusted efficiencies were, on average, different among the four regions). Contrariwise, the average adjusted efficiency was uniformly distributed over the 10 years from 2008 to 2017 (there was no difference across the 10 years).

Table 6.6 Wilcoxon Rank Sum Test of the US and Canada Region

Region	W-Test	The Asia-Pacific	Africa and the Middle East	Europe
US and Canada	Z	-3.0240	-2.8730	-3.0990
	P.Value	0.0025	0.0041	0.0019

Source: Atris (2020)

Table 6.6 presents the Wilcoxon rank sum test results, separately, between the US and Canada and the other three regions. The test investigates the null hypothesis (H_0) that the mean of the average adjusted efficiency level between the US and Canada and the other regions is equal. The results indicate that the Z statistics between the U.S. and Canada on one hand and the Asia-Pacific region, Europe, and Africa and the Middle East on the other are -3.0240, -2.8730, and -3.0990, respectively, with p-values of 0.0025, 0.0041, and 0.0019, respectively, at the 5% significance level. These results reject the null hypothesis (H_0) that there is no statistically significant difference in the average adjusted efficiency mean between the US and Canada and the other three regions.

Table 6.7 Wilcoxon Rank Sum Test of Europe

Region	W-Test	The Asia-Pacific	Africa and the Middle East	US and Canada
Europe	Z	0.1510	0.7560	-3.0990
	P.Value	0.8798	0.4497	0.0019

Source: Atris (2020)

Table 6.7 shows the Wilcoxon rank sum test statistics between Europe and the other three regions. The test investigates the null hypothesis (H_0) that there is no difference in means average adjusted efficiency levels between any two regions. The critical values (Z) between Europe and the Asia-Pacific region, Africa and the Middle East, and the U.S. and Canada are 0.1510, 0.7560, and -3.0990, respectively, and their p-values are 0.8798, 0.4497, and 0.0019, respectively, at the 5% significance level. Consequently, we do not reject the null hypothesis (H_0) that there is no statistically significant difference in average adjusted efficiency mean between Europe on one hand and the Asia-Pacific region and Africa and the Middle East on the other. Therefore, we reject the null hypothesis regarding the EU region and US and Canada, as shown in Table 6.6.

Table 6.8 Wilcoxon Rank Sum Test of Africa and the Middle East

Region	W-Test	The Asia-Pacific	Europe	US and Canada
Africa and the Middle East	Z	0.7560	0.7560	-2.8730
	P.Value	0.4497	0.4497	0.0041

Source: Atris (2020)

Table 6.8 shows the Wilcoxon rank sum results of the test between Africa and the Middle East and the other three regions. The test investigates the null hypothesis (H_0) that there is no difference in mean average adjusted efficiency levels between any two regions. The critical values (Z) between Africa and the Middle on one hand and the Asia-Pacific region, Europe, and the U.S. and Canada on the other are 0.7560, 0.7560, and -2.8730, respectively, and their p-values are 0.4497, 0.4497, and 0.0041, respectively, at the 5% level of significance. As a result, we do not reject the null hypothesis (H_0) between Africa and the Middle East and the Asia-Pacific region and Europe. This indicates that there is no statistically significant difference in average adjusted efficiency mean between Africa and the Middle East and the Asia–Pacific region and Europe. Therefore, we reject (H_0) between Africa and the Middle East and the US and Canada (see Table 6.6).

Table 6.9 Wilcoxon Rank Sum Test of the Asia-Pacific

Region	W-Test	Africa and the Middle East	Europe	US and Canada
The Asia-Pacific	Z	0.7560	0.1510	-3.0240
	P.Value	0.4497	0.8798	0.0025

Source: Atris (2020)

Table 6.9 shows the Wilcoxon rank sum results for the test between the Asia-Pacific region and the other three regions. The test investigates the null hypothesis (H_0) that there is no difference in mean adjusted efficiency level between any two regions. The critical values (Z) between the Asia-Pacific region on one hand and Africa and the Middle East, the EU, and the U.S. and Canada on the other are 0.7560, 0.1510, and -3.0240, respectively, and their p-values are 0.4497, 0.8798, and 0.0025, respectively, at a 5% significance level. Thus, we do not reject the null hypothesis (H_0) between the Asia-Pacific region and Africa and the Middle East and Europe. This indicates that there is no statistically significant difference in average adjusted efficiency mean between the Asia-Pacific region and Africa and the Middle East and Europe. Therefore, we reject (H_0) between the Asia-Pacific region and the US and Canada (see Table 6.6).

6.5 Summary of Chapter 6

This chapter investigated the efficiency of O&G refineries in four global regions—the US and Canada, the Asia-Pacific region, Africa and the Middle East, and Europe— over the period (2008-2017) using a unique unbalanced dataset comprised of 696 refineries operating in the four regions. The study utilized the averages of the refineries' adjusted efficiencies to simplify the discussion because the dataset was unbalanced and the sample was large. The study used a combination of DEA and DEA-DA to provide an efficiency-based ranking of the O&G refineries.

A KW rank sum test was used to test whether the average adjusted efficiencies measures differed among the four regions and if they changed over time. Furthermore, a Wilcoxon rank sum test was applied to investigate whether the average adjusted efficiency levels differed between any of the two regions over the study's 10-year sample period.

The results indicate that the US and Canada outperform the other three regions; this is followed by the Asia-Pacific region, Africa and the Middle East, and Europe, respectively. The chapter also found a statistically significant difference among the four regions. Moreover, the average adjusted efficiency ranks were invariant from 2008 to 2017. This result due to the differences between the refineries' types, technological complexity levels, and capacities: The US and Canada region achieved the best performance among the other regions due to its available advanced technologies[63] that allow refineries to extract light tight oil (LTO) as well as restrictive environmental regulations. Those advanced technologies give the US refineries a competitive advantage in adapting to global market changes and requirements.

Furthermore, the operations of integrated US oil companies (such as Majors) boost the region's global position through the many joint ventures being conducted with other countries. Vertical integration is a crucial factor in enhancing refinery efficiency because it reduces risks and increases profitability at every stage, from the wellhead to the gasoline station. Vertical integration and joint ventures also help refineries achieve a balance between conducting operations and protecting themselves against market instability.

A 2018 oil market report[64] stated that the US was expected to be a major player in massive integrated petrochemical projects for producing ethylene. This will help the US to not only cover the growth in its domestic market but also export to other markets. Further, the US and Canada will become the leading suppliers of crude oil over the next five years. The US will export LTO to Europe to address its deficit of African light oil and also to the Asia-Pacific region to satisfy the market demand for

[63] The technology differences among countries are related to refinery type and level of technology (refinery complexity) that utilized. In the US, for example, most of the refineries are conversion facilities of medium-to-high complexities. On the other hand, In Asia, the Middle East, and South America, which are experiencing rapid growth for light products and gasoline demand, almost all new construction is conversion and deep conversion facilities. Further, hydro skimming refineries are common in Europe, Japan, and Russia (Kaiser 2017).

[64] See the International Energy Agency (https://webstore.iea.org/market-report-series-oil-2018).

petrochemical raw material. This illustrates the vital role of vertical integration and resource proximity in refinery efficiency.

The Asia-Pacific region shows the highest O&G capacity and activity levels, as well as increasing adjusted efficiency trends. As a result, the Asia-Pacific region has become an attractive market for major oil companies, which are increasing their investments by engaging in many joint ventures, particularly in petrochemical plants.

Africa and the Middle East have also started to integrate their refineries through many joint ventures in order to generate more complex refining and petrochemical products domestically. That implies the importance of petrochemical and complex refining products, which are considered key to gaining more global market share, thereby enhancing refining efficiency.

Despite the expected refinery shutdown waves in Europe due to the IMO regulation in 2020, the demand for refinery products slightly increased in 2017 because of the global trend toward high-consuming vehicles (SUVs). This increase indicates that changes in demand patterns affect refinery products and that Europe should invest in technology in order to overcome their resource limitations.

Based upon the results, various management/policy recommendations were proposed to enhance the refineries' operational efficiency in each region. These include (1) Processing of incremental amounts of domestic LTO by US refiners is likely to have a positive impact on refinery efficiency. However, the US needs to import different qualities of crude oil to maximize its throughput, considering its mix of refining capacity. Hence, it would be uneconomic to run refineries only with light crude oil; (2) Adjustment of refinery structure and control the scale of industry is required to improve the scale efficiency of refined and petrochemical products, for instance, the Asia-Pacific region has to adjust their refineries capacity to adapt rising in petrochemical demand leads by China, India and Southeast Asia, particularly, in chemical products; (3) The future for oil producers lies in developing a value-added sector of refining and petrochemicals. Therefore, the Middle East region has to engage in many joint ventures through intensive capital investment to expand into the downstream sector and to refine its crude oil domestically, which creates more value from their crude oil throughput and diversify the region's economies; (4) The Asia-Pacific has to accelerate the application of new technologies to the refineries.

Whereas, turning heavy oil into high-quality products also requires more advanced molecular processing than is possible with simple refining or distillation; (5) European refineries have to launch joint ventures or cooperate with electric vehicle (EV) producers to offset their losses incurred when converting to other energy resources; (6) Europe region should not add more costs on the refining sector and stimulates R&D to unlock innovation to develop the low-carbon technologies for refineries and their products.

One limitation of this chapter is that it does not examine the effects of M&A policies on the global refining market. This issue will be discussed in future research as an extension of this chapter.

Chapter 7

General Discussion And Conclusion

7.1 Introduction

The evaluation of the O&G supply chain performance relates to various issues such as operational performance, environmental performance, and responses to the global market volatility. Therefore, the main purpose of this thesis was to evaluate the O&G supply chain management performance by examining the main supply chain segments upstream (E&P) companies, and downstream (refineries), as illustrated in detail in two central chapters. Further, the findings and the policy implications of the performance depending on deferent aspects; for instance, in chapter 5, the policy implications depend on both unified efficiency score & company type. However, in chapter 6, the policy implications depend on the adjusted efficiency score for every region and the regional characteristics.

In this chapter, the major findings concerning the research questions are summarized, and general conclusions based on the results of the main studies presented in this thesis are described. Further, the limitations of this thesis are considered, and suggestions for further research into The O&G are offered. This chapter concludes with recommendations and policy implications for three categories of the O&G industry stakeholders: managers, policy-makers, and individuals who are interested in the O&G industry. Moreover, this chapter uses the recommendation and future research possibilities to help answer the research questions raised in Chapter 1:

a. How can O&G upstream companies improve their environmental performance to meet the restricted environmental regulations, and to what extent can the type of company affect its environmental performance?
b. What are the main factors needed to improve the performance of the O&G upstream sector?
c. Is the efficiency performance of O&G refineries be affected by the region?
d. What are the main factors needed to enhance the performance of the O&G downstream sector?
e. Which segment of the O&G Industry can effectively adapt and meet the environmental regulations?
f. What are the recommended policies that could be supportive for O&G companies' managers to improve their efficiency?

7.2 Findings Concerning the Research Questions

7.2.1 Research question (a)

The answer to this question is presented in chapter 5 and covered by the second hypothesis, which proposed that the type of company could affect its environmental performance. Chapter 5 investigated the environmental and operational efficiencies of two types (integrated & independent) of E&P companies in the US, and the result of the study revealed that on average integrated companies outperformed the independent companies with regard to the environmental performance, which attributes to their vertical integration along with their supply chain from the upstream to the downstream segment where the vertical integration allows them to interact with their end-user customer's feedback regarding green products and avoiding the contaminated products. Thereby they could get quick responses to the environmental conscious for the end-user customers. Further, the integrated companies can work in global areas and quickly adapt to different kinds of environmental regulations.

However, the results of operational performance indicated that the independent companies outperformed the integrated ones for three years of five, which denoted that the firm's size and scale could not be indicators for operational efficiency. Further, the improvement of the operational efficiency of independent firms could be attributed to the specialization in one specific segment of the O&G industry (Pendley 2017).

7.2.2 Research question (b)

The answer to the question is discussed in chapter 5 in detail. The main findings proposed that vertical integration and working through the efficient supply chain and operational size were the main factors that could improve the unified efficiency of the upstream O&G companies. Where, the efficient SCM should maintain both sides of production outcomes, environmental protection, and minimizing operation costs, Agarwal et al. (2016). Further, expanding in capital expenditure and investments could enhance the overall efficiency performance.

7.2.3 Research question (c)

This question is investigated in chapter 6 and covered by the first and second hypothesizes, which proposed that the efficiency could vary depending on the regional location and characteristics. The significant finding confirmed the impact of region location on O&G refineries' operational efficiency, where the refineries' efficiency differed from region to another due to the regional circumstances (e.g., the proximity of resources, technology level, type of refineries, and demand patterns). For instance, the US & Canada refineries have shown the best performance among the four regions, which was due to the existence of majors O&G companies that use the highly advanced technology and abundance of shale oil resources there. On the other hand, Europe was the worst performance among the four regions due to the changes in their market patterns caused by the switchover to electric vehicles and buses and because Europe is moving toward a low-carbon economy and the use of fuel-mix energy. Further, there is a shortage of crude oil resources in Europe.

7.2.4 Research question (d)

The answer to this question is addressed in detail in chapter 6. The major findings addressed the main factors needed to improve the refineries' efficiencies. These main factors are (a) refinery complexity level, which helped to produce more purified and highly valued products; (b) vertical integration and joint ventures that improved the refineries' ability to achieve a balance between conducting operations and protecting themselves against market instability; (c) advanced technology applications that meet the new environmental regulation regarding the refineries; and (d) resource proximity, which plays a vital role by reducing the transportation cost.

7.2.5 Research question (e)

Regarding the O&G industry structure discussion in chapter 3, the upstream sector is the highly regulated sector among the O&G Industry segments, which faced the highly restricted environmental regulations. Further, as mentioned in chapter 5 that examined the unified efficiency of the O&G upstream companies in the US, all and facilities must apply their GHG emissions report to the EPA as a response to Greenhouse Gas Reporting Program (GHGRP)[65]. Besides, the other global E&P

[65] See: https://www.epa.gov/ghgreporting

companies also have to consider their environmental footprint and declare it in their annual sustainability reports.

7.3 Discussion and Policy Implications

The O&G industry is the primary source of global energy consumption. However, the O&G Industry faces operational, environmental, and global demand challenges through its competitive work environment. These challenges were the motivation for examining the O&G supply chain performance by examining the two main O&G industry segments in its supply chain by conducting the two central studies of the thesis as follows:

The first main study investigated the overall (environmental & operational) performance of O&G companies by examining the E&P companies (upstream sector) in the US using 34 O&G companies from 2011 to 2015. The study utilized a unique, balanced panel dataset; the dataset included seven majors O&G companies (integrated companies) and 27 independent companies. For measuring the unified efficiency, the study applied the non- radial DEA environmental models to the dataset. Further, The KW rank-sum test is utilized to examine whether UEN and UEM measures variant over time and whether there are differences between integrated and independent O&G firms.

The second main study examined the O&G refining companies (downstream sector) by investigating the efficiency of O&G refineries among four global regions over the period (2008- 2017). The study used a unique unbalanced dataset of 696 refineries globally. Further, the second study utilized a combination of DEA and DEA-DA to estimate an efficiency-based ranking of the O&G refineries. A KW rank-sum test was applied to test whether the average adjusted efficiencies measures varied among the four regions and if they changed over time. After that, a Wilcoxon rank-sum test was applied to examine whether the average adjusted efficiency levels changed between any of the two regions over the ten years. Moreover, the thesis was offered some recommended policies, which led to enhancing O&G companies' efficiency performance to meet the environmental regulations and global market requirements.

The significant new findings of the thesis concluded as follows:

1- The actual data and utilized models confirm the importance of supply chain management. Both upstream and downstream segments emphasized the importance of vertical integration and joint ventures that positively impact both the O&G main industry segments. Further, chapter 5 introduced some regulatory aspects that affect the efficiency level in the US.

2- Conducting regional comparison analysis using a combination of DEA and DEA-DA models is a unique application, which indicates the importance of regional technology differences and discuses its impact on the efficiency levels. In comparison, the previous O&G studies did not include this kind of application and discussion.

Possible implications of the O&G industry main sectors (upstream & downstream) are discussed in this section. Further, the answer to the research question (f) is covered by this section. These recommendations that could improve O&G are as follows:

- The corporates` leaders should be aware of their environmental footprints. That would give them financial advantage to increase their market share.

- The independent companies` mangers should improve the corporate image for consumer and considers their opinions on the corporate operational performance to boost sales because the consumers avoid products and services from dirty-imaged companies. Besides, managerial efficiency is a crucial factor in corporate sustainability.

- The upstream segment is the very complex and intensive investment sector; therefore, the expansion in capital expenditure and investments in technology could enhance the overall efficiency of the upstream sector.

- Vertical integration through efficient SCM could enhance the unified efficiency of the upstream O&G companies.

- Working along the O&G supply chain from upstream to downstream would improve the quick response to the end-user feedback.

- The US & Canada region needs to import different qualities of crude oil to maximize its productivity, considering its mix of refining capacity. Hence, it would be uneconomic to run refineries only with light crude oil.

- Adjustment of refinery structure and control the scale of the industry is needed to improve the scale efficiency of refined and petrochemical products, for instance, the Asia-Pacific region has to adjust their refineries capacity to adapt rising in petrochemical demand leads by China, India, and Southeast Asia, particularly, in chemical products.

- The oil producers' future lies in developing a value-added sector of refining and petrochemicals. Thus, the Middle East region has to engage in many joint ventures through intensive capital investment to expand into the downstream sector and to refine its crude oil domestically, which creates more value from their crude oil throughput and diversify the region's economies.

- The Asia-Pacific needs to speed the application of new technologies to the refineries. Whereas, turning heavy oil into high-quality products also requires more advanced molecular processing than is possible with simple refining or distillation.

- European refineries have to launch joint ventures or collaborate with electric vehicle (EV) producers to offset their losses incurred when converting to other alternative energy resources.

- Europe region should not add more costs to the refining sector and stimulates R&D to unlock innovation to develop the low-carbon technologies for refineries and their products.

7.4 Limitation of The Empirical Studies

The empirical study in Chapter 5 has two main limitations the first one regarding the sample size, where the study used a small sample size due to data availability issues. Further, the second limitation is that the study did not examine the emerging O&G market players who operate in the shale oil/gas business.

On the other hand, the empirical study in Chapter 6 is limited to M&A policies on the global refining market, where the study does not examine the effects of such kind of these policies and does not examine the impact of the new refineries' environmental regulation on the refineries' performance. Moreover, the technological differences among the countries are discussed based upon qualitative analysis and conceptual discussion because of the difference in technology among regions relates to many variables such as region or country regulations, business environment, amount of invested capital, demand patterns, etc. Further, to confirmed and technology differences, it is needed to conduct a qualitative analysis, e.g., second stage regression, using a technological dummy variable or technological index because the DEA does not consider that kind of difference.

7.5 Suggestions for Further Research into The O&G Industry

7.5.1. Future work related to the first empirical study:

The study sample can be expanded to cover other nations (OPEC and non-OPEC), not only the US. This expansion helps test the influence of corporate scale and supply chain on environmental efficiency to obtain a global perspective of the O&G upstream industry. Further, embedded new market players, e.g., shall players, would be interesting to investigate their efficiency performance as emerging players in the O&G market.

7.5.2. Future work related to the second empirical study:

Recently, M&A deals play an essential role in the company's formation and structure, which affects the refineries' performance. Therefore, examining of M&A impacts on the O&G refineries would be an interesting point that helps to evaluate the company performance deeply. Further, after the IMO environmental regulation was released, it would be interesting to investigate its impact on global refineries performance.

Over the above, due to the data constraints for the second stage regressions. An application of the second stage regression model as a future work could be conducted to determine the mechanism deeply behind the observed phenomena. Where the DEA model is conducted as a first stage of the computational framework, then the efficiencies scores obtained from DEA at the first stage are regressed in the second stage as a dependent variable, and some variables of interest are independent variables. Thereby, the second stage regression model, e.g., Tobit, bootstrapped, and fraction regression model (FRM), identifies the reason for being inefficient or the factor that affect the relative efficiency. One of the main dependent factors that could be considered in the second stage regression analysis is the Macroeconomic situation of the country, particularly the country's political situations. Of course, the country's political situation affects its productivity and the total amount of O&G supply, for example, in Venezuela, which has the most significant amount of oil reserves in the world with 300.9 billion barrels. Furthermore, it has an abundant supply of natural resources; the country still struggles the US sanctions impacts on its petroleum industry. Although Venezuela has the most oil reserves globally, most of its oil is offshore or far underground and considered dense. Therefore, the extracting cost of crude oil in Venezuela's reserves is too high to be profitable. Moreover, US sanctions on the Iranian O&G industry restricted the amount of crude oil supply, affecting the global crude oil price and the industry segment. Further, the unstable political situation between Saudi Arabia and Iran and the other Middle East region conflicts lead to a more volatile market situation that affects all industry performance from upstream to downstream.

7.5.3 Future work in the short-term

Artificial Intelligence (AI) technologies will have transformative impacts on the O&G industry in light of the big data and massive technology era[66]. AI can deliver value more effectively and efficiently, positively changing the performance of O&G companies and leading to growth for the next decades. The O&G industry has two major applications of the technology: machine learning and data science. Recently, some giant O&G companies are using AI tools as solutions to cut their operating costs through automating functions. For instance, Bp multinational company installed an AI program that monitors data from sensors attached to the pump and flags glitches before they cause a shutdown to avoid any operation problems[67]. Further, in February 2019, ExxonMobil launched a partnership with Microsoft Corp. To apply AI programs to maximize its operations in the Permian, or West Texas Basin. ExxonMobil also announced a partnership with the MIT to design AI robots for ocean exploration, which it wants to use to develop its natural seep detection abilities[68].

Therefore, the future work plan is going to deal with these technologies trajectories through investigating the impacts of AI and Machine learning applications on the O&G industry performance from the upstream sector (E&P) to downstream sectors (refining & marketing). Besides, the future work plan is going to try to answer this question to what extent the application of AI and machine learning can enhance the overall efficiency of O&G companies. For that objective, I proposed to apply DEA methods to evaluate the overall performance of the O&G companies by using AI technologies as a significant input. DEA methods would be utilized to estimate two types of companies' performance (environmental and operational) to investigate the impact of AI application on the overall efficiency.

[66] See appendix A for the recent technology tends of the O&G industry.
[67] https://www.wsj.com/articles/oil-and-gas-companies-turn-to-ai-to-cut-costs-11571018460. (Accessed in December 14 the 2019)
[68] https://www.oilandgasiq.com/strategy-management-and-information/news/is-ai-the-next-revolution-for-the-oil-and-gas-industry. (Accessed in December 14 the 2019)

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Appendix A

A.1. Technology Trends of O&G Industry

Recently, the digital (software) technology has reshaped many global industries, and it becomes essential to embrace the latest trends of the digital technologies revolution. As a result of digital innovations technologies, The O&G industry is undergoing a massive transformation. Where the O&G industry has lagged a bit for adopting digital technologies compared with the other industries. Further, the digital technologies trend in the O&G industry is a part of the escalating trend that argues O&G companies to make collaborative arrangements and partnerships, mainly focused on utilizing emerging opportunities in areas, e.g., logistics, supply chain integration, and trading and payments. As the O&G companies navigate through this digital environment, they are keeping their digital conversion with a view to drive efficiency, growth, productivity, and safety for their operation, while also maintaining their endeavors to explore new business models. Against this background, the recent O&G industry key technology trends are summed up as follows:

A.1.1 Digital Oilfield

The concept of digital oilfield combines digital technologies with business process management to automate the O&G field operations for maximizing productivity and minimizing the overall associated risks, thus reducing the cost and increasing the profit[69]. The adoption of this concept allows O&G companies to establish a 'digital twin' that duplicates and connects the performance of an oilfield on a computer database. Further, the digital oilfield aims to promote the O&G sector's appeal by combining operational technology with information technology, particularly in a low oil price environment. The leaders' key players of this technological trend theme are multinational companies, e.g., BP, Shell, Chevron, Equinor, and oilfield service providers, e.g., Schlumberger, Halliburton, Baker Hughes, and Weatherford.

69 See: (https://www.offshore-technology.com/comment/digital-oilfield-of-the-future/)

A.1.2 Increasing Adoption of IoT Devices and Electronic Monitoring

O&G upstream and downstream segments will continue to raise their adoption of advanced and sensitive sensors such as drones, with a considerable ratio of the resulting data being gathered from edge computing devices and controlled by "data historians" as the core of a data system. Further, IT will lead to a significant role in handling the device connectivity, data processing and application workloads both on the edge IoT platforms and the cloud. Besides, it can help O&G companies foresee equipment failure and reduce overall downtime.

A.1.3 Blockchain Technology

Blockchain technology is expected to have a significant impact on the O&G industry though cutting down operating time and costs, while also adding more transparency to the industry. As the O&G industry is gradually moving toward Artificial intelligence (AI) and digitalization, many large O&G corporations were working on blockchain technology in the past two years because of it can significantly evolve the management level, efficiency, and data security of the O&G industry, LU *et al.* (2019). Further, the technology recently is received great attention when a group of seven O&G companies, including ExxonMobil and Chevron, agreed to compose the first industry blockchain association, which aims to explore the potential advantages that blockchain technology can offer to the O&G industry[70].

A.1.4 Fleet-Management Solutions

It is hard to Keep track of employees and equipment. Recently, with the help of GPS tracking, remarkable data can be gathered and viewed nearly instantaneously, even in the utmost remote locations. This technology trend helps the O&G company to know exactly where all of its expensive equipment is at all times and can be warned if something is out of place.

[70] See: (https://globuc.com/news/7-ways-blockchain-can-revamp-the-oil-and-gas-industry/)

Appendix B

B.1 DEA Conventional Models

It is hard to find the cost of each input and the price of each output in the relative efficiency model so that particular cost and price could be given to each input and output, respectively. Moreover, the various DMUs control their process differently hence value their inputs and outputs differently, which leads to differing weights. To overcome these drawbacks, Charnes, Cooper, and Rhodes (1978) first proposed a mathematical programming approach that defined the weights of inputs and outputs and computed the efficiency score. Then, A significant stage in a DEA measurement is the identification of the input/output variables related to the DMUs being assessed. See, Boussofiane *et al*. (1991).

B.1.1 Charnes, Cooper, and Rhodes (CCR) Model (Input-Oriented)

CCR is a Fractional-programming model; it was proposed by Charnes *et al.* (1987), which had an input orientation to determine the efficiency level of each of the DMUs in a data set of comparable units. The CCR model indicates the ideal set of weights for each DMU when the problem is solved for each DMU under consideration. CCR model provides an objective evaluation of overall efficiency and assumes constant returns to scale (CRS). The structure of the model is presented as follows:

$$max\ h_0 = \frac{\sum_{r=1}^{s} u_r y_{rj_0}}{\sum_{i=1}^{m} v_i x_{ij_0}} \quad for \quad DMU_0$$

$$subject\ to\ \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \quad j = 1,2,\dots,n, \qquad \text{(B.1)}$$

$$v_i \geq 0 \qquad i = 1,2,\dots,m,$$

$$u_r \geq 0 \qquad r = 1,2,\dots,s.$$

Where v_i *and* u_r are weights assigned to outputs y_{rj} and inputs x_{ij}, respectively, to maximize the efficiency score h_0 for DMU_0, the constraints supposed that the efficiency score should not exceed 1 for any DMU and weights should be positive and their lower bounds are zeros.

The previous formulation of the CCR model is a fractional program and it has to switch to a linear program for solving the problem efficiently. Using a normalization, i.e., the denominator is removed from the objective function and instead, an additional constraint is added, the model is modified as follows:

$$
\begin{aligned}
& max\ h_0 = \sum_{r=1}^{s} u_r y_{rj_0} \quad \textit{for DMU0} \\
s.t.\quad & \sum_{i=1}^{m} v_i x_{ij_0} = 1 \qquad \text{(B.2)} \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0 \quad j= 1,2,\ldots,n, \\
& v_i \ge 0 \quad i= 1,2,\ldots,m, \\
& u_r \ge 0 \quad r= 1,2,\ldots,s.
\end{aligned}
$$

Here, this primal linear program model is called a multiplier model due to the modification from the fractional program to the linear program and the input and output variables are multiplied with their particular weights. This CCR model expresses the input-oriented DEA model. By adding an Archimedean number (ε) as a weight restriction instead of zero in the CCR, all DMUs assure that none of the assigned weights are equal zero, which confirms that all variables are considered while determining the efficiency score, Pasupathy (2002). From a computational point of view, the primal model is more challenging to solve than the dual model[71]. The dual of this CCR model is obtained by assigning a variable to each constraint and transforming the limitations. The dual is known as the envelopment form, which is shown below.

$$
\begin{aligned}
& min\ \theta \qquad for\ DMU_0 \\
s.t.\quad & \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{rj_0} \quad r=1,2,..,s, \qquad \text{(B.3)} \\
& \theta x_{ij_0} - \sum_{ji}^{n} \lambda_j x_{ij} \ge 0 \quad i=1,2,\ldots,m, \\
& \lambda_j \ge 0 \qquad j=1,2,..,n.
\end{aligned}
$$

[71] The CCR primal model has m+s variables and 1+n+m+s constraints. The dual would have n+m+s+1 variables and s+m constraints. Hence n is quite large compared to m+s. thereby the primal has a large number of constraints compared to the dual that indicates the primal is more difficult to solve (see Pasupathy (2002))

Where λ_j is the weights of the DMU_j.

By adding slack variables, the dual problem becomes:

$$\min \theta - \varepsilon\left(\sum_{r=1}^{s} s_r^+ + \sum_{i=1}^{m} s_i^-\right) \quad \textit{for } DMU_0$$

$$\begin{aligned} s.t. \quad & \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{rj_0} && r=1,2,..,s, \qquad \text{(B.4)} \\ & \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{ij_0} && i=1,2,...,m, \\ & \lambda_j \geq 0 && j=1,2,..,n, \\ & s_i^-, s_r^+ \geq 0 \ \& \ \theta \text{ unrestricted.} \end{aligned}$$

Where the slacks variables (s_i^-, s_r^+) here represented the input overconsumption and the output shortfall, respectively, compared to the efficient frontier.

B.1.2 CCR Output-Oriented Model

Mutually, it could be started with the output side and considered the ratio of input to output instead. This ratio change would redirect the objective from max to min, as in (4), to get the following form of CCR output-oriented:

$$\min q_0 = \sum_{i=1}^{m} v_i x_{ij_0} \quad \textit{for } DMU_0$$

$$\begin{aligned} s.t. \quad & \sum_{r=1}^{s} u_r y_{rj_0} = 1 && \text{(B.5)} \\ & \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 && j=1,2,...,n, \\ & v_i \geq 0 && i=1,2,...,m, \\ & u_r \geq 0 && r=1,2,...,s. \end{aligned}$$

Then, the dual model of CCR output-oriented could be expressed as shown below.

$$\max \emptyset + \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \quad \textit{for } DMU_0$$

$$\begin{aligned} s.t. \quad & \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = \emptyset y_{rj_0} && r=1,2,..,s, \qquad \text{(B.6)} \\ & \sum_{ji}^{n} \lambda_j x_{ij} + s_i^- = x_{ij_0} && i=1,2,...,m, \\ & \lambda_j \geq 0 && j=1,2,..,n, \\ & s_i^-, s_r^+ \geq 0 \ \& \ \theta \text{ unrestricted.} \end{aligned}$$

B.1.3 Variable Returns to Scale (VRS) or BCC Model

BCC model is the first extension of the CCR model, it was proposed by Banker, Charnes and Cooper (1984) by adjoining the constraint $\sum_{j=1}^{n} \lambda_j = 1$ to account the VRS. The BCC model differentiates between technical and scale inefficiencies by measuring pure technical efficiency at the given scale of operation. Further, it determines whether increasing, decreasing, or CRS possibilities are present for further exploitation. The envelopment (dual) form of the BCC model would be the same as the CCR model formation with an additional constraint $\sum_{j=1}^{n} \lambda_j = 1$. The structure of the BCC model is given by the linear program form as follows:

$$
\begin{aligned}
& \min \theta \qquad \textit{for } DMU_0 \\
s.t. \quad & \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r_{j0}} \qquad r=1,2,..,s, \qquad \text{(B.7)} \\
& \theta x_{ij_0} - \sum_{ji}^{n} \lambda_j x_{ij} \geq 0 \quad i=1,2,...,m, \\
& \sum_{j=1}^{n} \lambda_j = 1 \qquad j=1,2,..,n.
\end{aligned}
$$

By adding slack variables, the dual problem becomes as in (4):

$$
\begin{aligned}
& \min \theta - \varepsilon\left(\sum_{r=1}^{s} s_r^{+} + \sum_{i=1}^{m} s_i^{-}\right) \quad \textit{for } DMU_0 \\
s.t. \quad & \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^{+} = y_{r_{j0}} \qquad r=1,2,..,s, \quad \text{(B.8)} \\
& \sum_{ji}^{n} \lambda_j x_{ij} + s_i^{-} = \theta x_{ij_0} \qquad i=1,2,...,m, \\
& \sum_{j=1}^{n} \lambda_j = 1 \qquad j=1,2,..,n, \\
& \lambda_j \geq 0,\ s_i^{-}, s_r^{+} \geq 0 \ \&\ \theta \text{ unrestricted.}
\end{aligned}
$$

The significant difference between CCR and BCC models is the introduction of the convexity condition $\sum_{j=1}^{n} \lambda_j = 1$. The additional constraint affords the frontiers piecewise linear and concave characteristics. As shown in Figure 4.1.[72]This figure represents the difference between production possibility sets in both cases CRS and VRS. Where The CCR model is building on the assumption of CRS, which means that positive or negative economies of scale could not exist. Therefore, the BCC model is proposed to overcome this problem.

[72] Source: see Pasupathy (2002)

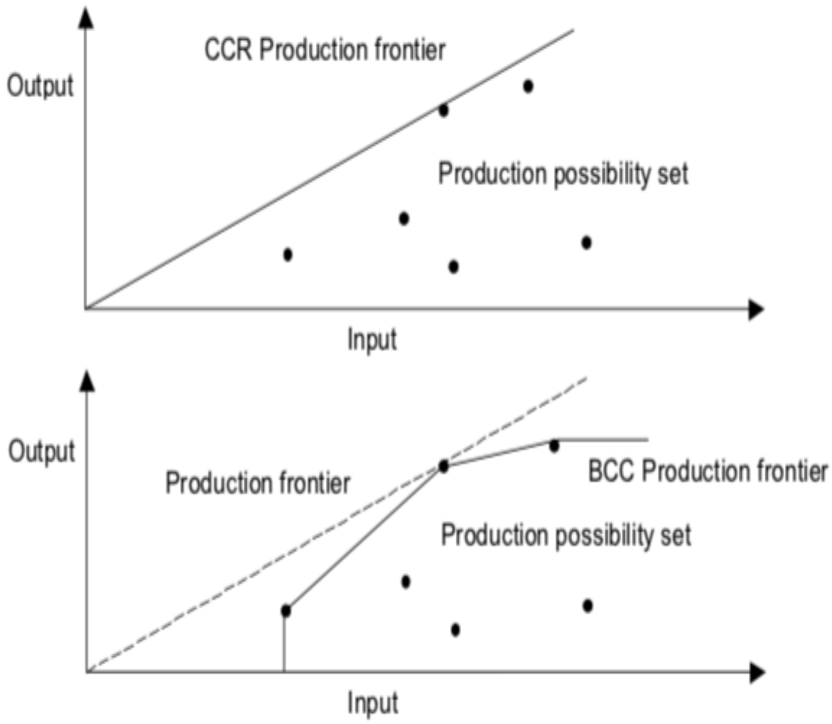

Figure B.1 CCR and BCC models

B.2 Slakes Based Model (SBM)

The SBM model is the second adjustment of the CRS model, it was proposed by Tone (2001). The purpose of the SBM model is to minimize the input and output slacks. Further, the model is used as the basis for the determination of super-efficiency. Efficiency is measured only by additional variables s^+ and s^-. The model formula, provided CRS is as follows:

$$
\begin{aligned}
& min\rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{s_i^-}{x_{io}}}{1 - \frac{1}{s}\sum_{r=1}^{s} \frac{s_r^+}{y_{ro}}} \\
& s.t \quad X\lambda + s^- = x_{io} \\
& \qquad Y\lambda - s^+ = y_o \\
& \qquad \lambda \geq 0,\ s^- \geq 0,\ s^+ \geq 0.
\end{aligned} \tag{B.9}
$$

Where s^-, s^+ are slacks represent input excess and output shortfall, respectively. The numerator and the denominator of the objective function of the SBM model gauge the average distance of inputs and outputs, respectively, from the efficiency threshold. Further, by appended the constraint $\sum_{j=1}^{n} \lambda_j = 1$ to the model (B.9) formula the model would be consistent with the BCC model.

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