UNIVERSITY OF GHANA

COLLEGE OF HUMANITIES

ACCOUNTING FOR ENVIRONMENTAL FACTORS IN ENERGY EFFICIENCY ANALYSIS

BY

ISSAH ABDUL BAAKI

(10417542)

A THESIS SUBMITTED TO THE DEPARTMENT OF OPERATIONS AND MANAGEMENT INFORMATION SYSTEMS, UNIVERSITY OF GHANA BUSINESS SCHOOL, UNIVERSITY OF GHANA, IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF MASTER OF PHILOSOPHY (MPHIL) DEGREE IN OPERATIONS MANAGEMENT

JULY 2019

DECLARATION

I, Issah Abdul Baaki, hereby declare that this thesis is the result of my research undertaken at the University of Ghana Business School. This thesis has not been presented by any other person, either in part or in whole, by any other person for any academic award in this or any other university. References to the publications of the work of other people have been fully acknowledged. I, therefore, declare that I bear the sole responsibility for any shortcomings of this research.

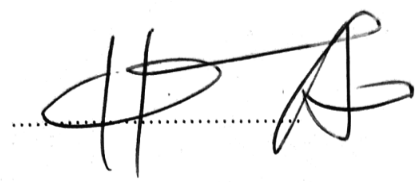
06/06/2020

ISSAH ABDUL BAAKI DATE

(10417542)

CERTIFICATION

We hereby certify that this thesis was supervised in accordance with procedures laid down by the University of Ghana.

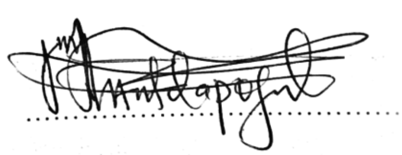


16/06/2020

……………………………… … ..…………………………

DR. KWAKU OHENE- ASARE DATE

(SUPERVISOR)



…………………………… ..……16/06/2020……………………

DR. ANTHONY AFFUL- DADZIE DATE

(CO -SUPERVISOR)

DEDICATION

I dedicate this work to my Family.

Special dedications also to Mr. Frank Issah Apaka and Mrs. Rose Jemilatu Issah for their immense support throughout my education.

ACKNOWLEDGEMENT

I am thankful to God Almighty for his wisdom and mercies throughout my years of study. I owe it all to the almighty God for His grace and for seeing me through another phase of life. My deepest gratitude goes to my principal supervisor, Dr. Kwaku Ohene-Asare and Co-supervisor Dr. Anthony Afful-Dadzie, both of the Department of Operations and Management Information Systems of the University of Ghana Business School, for their guidance, constructive criticisms and sacrificial support which made this work possible. I cannot forget the valuable contribution of Miss Evelyn Lamisi Asuah to the completion of this work. I truly appreciate her advice, time and comments offered to refine this work. Further appreciation goes to Dr. Francis Y. Banuro, Dr. Amin Karimu, and to all other lecturers and staff of the Department of Operations and Management Information Systems for their support.

Finally, my heartfelt thanks goes to my parents, siblings, colleagues and friends who have supported me in diverse ways to make this work possible.

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AFR	Africa
ASI	Asia
AUS	Australia & Oceanian
CO2	Carbon dioxide emissions
CH4	Methane emissions
CRS	Constant returns to scale
dc	Direct current
DEA	Data envelopment analysis
DMU	Decision making Units
ED	Economic development
EE	Efficiency and economic
ESTR	Energy savings target ratio
EUR	Europe
FDH	Free disposal hull
FE	Fixed effect
GDP	Gross domestic product
GHG	Greenhouse gas
GMM	Generalized Methods of Moments
GNIP	Gross national income per capita
Gw	Giggawatt
HDI	Human Development Index
IEA	International Energy Agency
INF	Inflation
IMF	International Monetary Fund

Kg	Kilogram
Kt	Kiloton
Max	Maximum value
Min	Minimum value
MPI	Malmquist Productivity index
Mtoe	Million Tonnes of Oil Equivalent
Mw	Megawatt
NAM	North America
N2O	Nitrous oxide
PPP	Purchasing Power Parity
POPG	Population Growth
RE	Random effect
RTS	Returns to scale
SAM	South America
SBM	Slack Based Measure
SO2	Sulfur dioxide
Std. Dev.	Standard Deviation
SZAL	Simar-Zelenyuk-adapted-Li
Twh	Terawatt Hour
TFEE	Total factor energy efficiency
TFEPI	Total factor energy productivity index
VIF	Variance inflation factors
VRS	Variable returns to scale
WDI	World Development Indicator

TABLE OF CONTENT

ABSTRACT

This study utilizes a nonparametric DEA approach, to assess the energy efficiency of 135 selected countries across the globe during the period of 2000 - 2014 to account for environmental factors in energy efficiency analysis and to analyze the relationship between economic factors and energy efficiency within a two - stage framework. Three kinds of variables are used: input, desirable output, and undesirable output. The inputs are labor, capital, and energy consumption. The undesirable outputs (environmental factors) are Carbon dioxide (CO_2), methane (CH_4) and Nitrous oxide (N_2O) emissions, the desirable output variable is gross domestic product (GDP). Energy efficiency is measured within a total factor framework by way of an SBM-Undesirable model. The second stage assesses the determinants of energy efficiency in countries by way of a bootstrapped truncated regression, FE, 2SLS and Systems Generalized Methods of Moments to control for possible heteroscedasticity, autocorrelation and endogeneity.

The results showed that the selected countries are on average 39% energy efficient within the study period, suggesting that increasing the levels of energy consumption in countries is not being used to produce the maximum GDP possible. The results also showed that incorporating the environmental factors improves the efficiency scores. Income per capita (GNIPC) and CAPLAB (Technological progress) are found to have significantly positive effects on energy efficiency of the countries, whilst higher debt stock and population growth leads to higher inefficiency given their negative significant relationship with energy efficiency.

CHAPTER ONE

INTRODUCTION

1.0 Background of the study

Energy has become the wheels on which all economies drive as it is a key factor used in the production of almost all goods and services (Narayan & Smith, 2008; Odhiambo, 2009; Wolde-Rufael, 2009). According to the World Resources Institute, the use of energy is the major cause of greenhouse gas emissions and global warming and accounts for 61.4% of total greenhouse gas emissions (Sadorsky, 2010).

In the light of increasing globalization, environmental concerns have captured serious attention from both governments and international organizations as production processes are accompanied by certain bad outputs from production processes (Al-Tuwaijri, 2004; Cherchye, Rock, & Walheer, 2015; Chiu, Liou, Wu, & Fang, 2012; K. Wang, Lu, & Wei, 2013). There is therefore the need for environmentally efficient production processes.

Environmental efficiency is of interest to every nation, due to the increase in emissions associated with the environmentally unsustainable production processes in most economies (Zaim & Taskin, 2000). Though the term environmental efficiency might mean different things to different people, it is simply defined as using less inputs to produce outputs with minimal environmental concerns (Pittman, 1983). Therefore, Environmental efficiency is seen as a necessary condition for economic and social development (Bai-Chen, Ying, & Qian-Qian, 2012; Halkos & Petrou, 2019).

In the development and economic growth of most economies, energy is one key factor that plays an essential role and has therefore become a fundamental part of global economic life (Barros & Assaf, 2009; Cleveland, 1997; Kashani, 2005; Murphy & Hall, 2011; Ramachandra, Loerincik, & Shruthi, 2006). Countries consume energy in their production processes which has both positive and negative impact on the environment such as greenhouse-gas emissions which is a threat to the world climate (Stern, 2007). This pollution growth has heightened global concern for climate change. This led to the September 2015 adoption of the 17 Sustainable Development Goals (SDGs) to be accomplished by 2030, among which is the crucial call to *"take urgent action to combat climate change and its impacts"* (SDG 13) (United Nations Environment Programme, 2016).

According to the Intergovernmental Panel on Climate Change (IPCC), the unprecedented increase in the global greenhouse gas (GHG) emissions in recent years is mainly driven by economic and population growth (IPCC, 2014). The IPCC (2014) reported that more than half of the average global temperature observed from 1951 to 2010 was caused by these gases; carbon dioxide (CO2), methane (CH4), nitrogen oxide (N2O) and the fluorinated gases (F-gases).With the strong growth of emerging economies such as China and India, reliance on energy is expected to further increase heavily (Barros & Assaf, 2009) leading to a rise in the concerns on global warming (Zhang, Cheng, Yuan, & Gao, 2011).

Fare, Grosskopf, Lovell, and Pasurka (1989) posit in their weak disposability assumption that production processes will always be accompanied by some undesirable output such as carbon dioxide (CO_2), sulfur oxide (SOX) and nitrous oxide (N2O) that are detrimental to the natural environment. As economies rapidly expand and businesses increase their demand for energy, there is an increase in the green- house emissions, as the desirable output is accompanied by some bad outputs. Since these green-house emissions and other air pollutants derived from the consumption of energy is a major contributor to global warming and regional atmospheric contamination, academic researchers, industry entrepreneurs and government officials, have recently recognized that sustainable development is one core solution to balance economic and social development with environmental protection and climate change mitigation (Zaim & Taskin, 2000).

Growing demands for environmental quality has forced policy-makers to consider the consequences of their actions in the formulation of economic policies. As environmental concerns are pronounced increasingly in relation to global warming, it is treated as an international matter (Zaim & Taskin, 2000) and therefore it is necessary to put in substantial effort to enhance environmental efficiency in this sector so as to cope with the massive demand and combat these green-house emissions.

Energy efficiency can be defined as the use of less energy to produce the same amount of some useful output (Ang, 2006). Therefore, an entity that is able to use less amount of energy inputs to produce the same amount of "useful outputs" is said to be energy efficient (Patterson, 1996). Environmental efficiency on is simply defined as using less inputs to produce outputs with minimal environmental concerns (Pittman, 1983).

Although many studies abound in energy efficiency (Adom, 2019; Alberini, 2018; Apergis, Aye, Barros, Gupta, & Wanke, 2015; Jebali, 2017; Keho, 2016; Moncef Krartia, 2018; Ohene-Asare & Turkson, 2018; Shen, 2017; Zhou, Ang, & Poh, 2008; Zhu & Chen, 2019), only a few (Ang, 2006; Chang, 2013; Chontanawat, Hunt, & Pierse, 2008; Hsieh, Lu , Li , & Xu, 2019; Oh & Lee, 2004; Ohene-Asare & Turkson, 2018; Pao & Tsai, 2010, 2011; Yang & Wei, 2019; Yongming Han 2018; Zhang et al., 2011) captured the negative externalities of energy use such as global warming. But none to the best of the authors knowledge has focused specifically and wholly on all continents across the globe, although some have included some African countries in their analysis (Adom, 2019; Ohene-Asare & Turkson, 2018; Ramanathan, 2005; Zhang et al., 2011) , Jebali (2017) and Hsieh, et al. (2019) covered only the Mediterranean and European countries respectively, even though country-specific benchmarks are necessary since levels of energy efficiency vary considerably among countries (Song, Yang, Wu, & Lv (2013). The purpose of this study is to evaluate the environmental energy efficiency of countries by using the slacks-based measure of Tone (2001). Next, the study investigates the economic and risk factors that can affect the efficiencies of the countries using truncated bootstrapped regression.

1.1 Problem statement

Resources used in productive processes which promote economic growth usually have some level of tamper on the quality of the environment. A study by Stern (2008), reports that a 1% increase in scale (economic growth) results in a 1% increase in emissions. Hence there is the need for sound, efficient and sustainable management of the environment. Globally, CO2 emissions have been of major interest to environmentalists and environmental economists as compared to other emissions such as SO2, NOX and so on. Human beings produce CO2 by burning fossil fuels such as coal, oil and gas in their commercial and domestic activities. Given the growing usage of fossil fuels for the production of goods and services, (CO2) emissions have increased significantly in the past century (Boopen, 2010) and accounts for about 72% of emitted greenhouse gases (Sanglimsuwan, 2011). Globalization is likely to increase trade volumes, expand economic activities and affect environmental quality (Vutha, 2008). Su (2011) opined that emissions in a country ‘s globalization processes measured as a percentage of its total emissions are increasing overtime.

Despite the many energy efficiency related studies (Adom, 2019; Alberini, 2018; Halkos & Petrou, 2019; Hsieh, et al. 2019; Iftikhar, Wang, Zhang, & Wang, 2018; Keho, 2016; Kounetas &

Zervopoulos, 2019; Shen, 2017; Wang, Duan, Ma, & He, 2019; Chen, Shang, & Wu, 2018; Yang & Wei, 2019; Yongming Han 2018; Zhongshan Yang, 2019; Zhu & Chen, 2019), this study identifies some gaps in the recent literature.

First, although country and cross country level energy efficiency studies exist (Adom, 2019; Apergis et al., 2015; Chang, 2013; Gómez-Calvet, Conesa, Gómez-Calvet, & Tortosa-Ausina, 2014; He, Zhang, Lei, Fu, & Xu, 2013; Honma & Hu, 2014b; Hsieh, et al., 2019; Hu & Wang, 2006; Keho, 2016; Li & Hu, 2012; Moncef Krartia, 2018; Rao, Wu, Zhang, & Liu, 2012; Song et al., 2013; Zhao Xiaoli, Yang Rui, & Ma Qian, 2014; Zhang, Kong, & Yu, 2015; Zhang et al., 2011; Zhongshan Yang, 2019), these studies fail to account for the effects of the bad output in the fuel burning process on the quality of the environment hence the results may not prove effective when assessing environmental-friendly energy efficiency. To take into account the growing concern regarding environmental impact, undesirable output should be incorporated into the environmental DEA framework, but none of the known energy efficiency studies to the best of the author's knowledge, has simultaneously incorporated undesirable outputs and applied bootstrapping (IEA, 2015; Li & Hu, 2012) though Jebali (2017); Song, Zhang, Liu, and Fisher (2013); Zuckerman, Welch, and Pope (1990) applied bootstrapping, Halkos and Petrou (2019); Hsieh, et al. (2019); Iftikhar et al. (2018); Kounetas and Zervopoulos (2019); Ohene-Asare and Turkson (2018); Wu et al. (2018) incorporated bad output in their study of countries. The bootstrap helps to purge the efficiency estimates of sampling variations resulting in reliable confidence interval for the estimates and produces estimates that mimic the true efficiency score (Simar & Wilson, 1998, 2000). Again, incorporating undesirable outputs gives a better efficiency assessment since energy production and use account for two-thirds of the world's greenhouse gas (GHG) emissions (IEA, 2015; Li & Hu, 2012).

Second, the traditional DEA models applied by some studies (Eller, Hartley, & Medlock, 2011; Ike & Lee, 2014; Sueyoshi & Goto, 2012b; Thompson, Lee, & Thrall, 1992; Wolf, 2009) failed to incorporate non-radial slacks which in the evaluation of efficiencies of Decision Making units (DMUs) has a high discriminatory power and seem to be more effective in measuring environmental efficiency than the radial efficiency measure which often leads to the case where a lot of DMUs have the same efficiency score of 1 and hence difficulty in ranking the environmental performance of these DMUs. Although a number of non-radial DEA models under the traditional DEA framework for instance, (Banker, 1986; Chen, 2003; Ray, Seiford, & Zhu, 1998; Zhu, 1996) have been developed, few studies have investigated how it is being applied in environmental efficiency assessment to the best of the authors knowledge (Peng Zhou, Poh, & Ang, 2007). It is therefore important to extend the traditional non-radial DEA models into the case where bad outputs exist.

Third, most energy efficiency studies use Tobit or Ordinary Least Squares (OLS) regressions to regress second stage environmental variables on first stage efficiency scores (Apergis et al., 2015; Boyd & Pang, 2000; Chien & Hu, 2007; Fang, Hu, & Lou, 2013; Honma & Hu, 2014b; Zhao Xiaoli et al., 2014; Zhang et al., 2011) which have been heavily criticized by Simar and Wilson (2007, 2011) as suffering from serial correlation and no proper data generating process leading to biased estimates and hence suggested the bootstrapped truncated regression analysis. Despite the popularity of truncated regression used in empirical works (Barros, Nektarios, & Assaf, 2010; Du, Worthington, & Zelenyuk, 2018; Kenjegalieva, Simper, & Weyman-Jones, 2009; Lu, Wang, & Kweh, 2014; Luhnen, 2009), it has also been criticized that the restrictive assumptions under truncated regression is not realistic under empirical setting (Banker, Natarajan, & Zhang, 2019). Therefore, OLS is argued to be more appropriate for second stage efficiency analyses because it is more robust than Tobit technique and truncated regression (Banker et al., 2019;Banker & Natarajan, 2008; Hoff, 2007; McDonald, 2009). Following, McDonald (2009), Banker et al. (2019) and Rajiv D Banker and Natarajan (2008), this study employs OLS in the second stage efficiency analyses. Similar to Alhassan and Ohene-Asare (2016), efficiency scores are logged in the second stage analysis and then estimated with OLS-PCSE to correct for autocorrelation and heteroscedasticity. Random Effect (RE), Fixed Effect (FE), Two stage least squares (2SLS) and two- step system Generalized methods of movements (GMM) are further used for robustness test.

Forth, few efficiency studies test for returns to scale(Gómez-Calvet et al., 2014; Mahlberg & Url, 2010; Tortosa-Ausina, Armero, Conesa, & Grifell-Tatjé, 2012). Testing for returns to scale(RTS) is important because the type of RTS selected in efficiency analysis can affect the efficiency results (Simar & Wilson, 2002). In the energy efficiency literature, to the best of the author's knowledge, only (Gómez-Calvet et al., 2014) empirically tested for scale elasticity.

Lastly, this study seeks to measure group efficiency of the countries based on their continental groupings. It is worth noting that different groups could exhibit possible technology heterogeneity originating from differences in infrastructure, resource endowment, firm-specific characteristics and other environmental factors which can affect their efficiency (Oh & Lee, 2010).

1.2 Research Contributions

The study makes important contributions to policy, practice and literature. On the policy side, by empirically assessing the environmental performance in the energy sector of countries, policy makers may have a reference for drafting energy efficient policies, based on the findings and recommendations. The analysis may provide insights into potential avenues for policy prescriptions and enhancement on issues on environmental efficiency which can then be oriented towards specific underperforming energy consuming countries. For practice, the results of the analysis will be beneficial to country managers of energy when they need to decide whether investing in energy use is an important performance driver in order to make important managerial decisions on this and other environmental conditions as to whether they should focus on them or divert resources away from them.

The research contributes to academic literature in three folds. First, the study extends the existing literature by premiering the empirical environmental energy efficiency study across the globe. Second, the study contributes to the current theoretical study on energy efficiency by becoming the first to assess the environmental energy efficiency of countries across all continents incorporating undesirable output. Lastly this is the first cross-country environmental energy efficiency study to the best of the authors' knowledge to adopt the second-stage OLS-PSCE, FE and System GMM regression to investigate the economic factors that can affect the efficiency of the countries.

1.3 Research Objectives

The main objective of the research is to assess the energy efficiency of countries incorporating environmental factors.

The specific objectives are as follows:

1. To test the scale elasticity property in the energy sector of countries.
2. To estimate the energy efficiency of countries incorporating environmental factors.

3. To statistically compare the bootstrap TFEE of countries with and without environmental factors.

4. To examine the dynamic productivities of the countries with and without environmental factors.

5. To assess the efficiency of the countries based on continental groupings.

6. To assess the effects of economic factors (inflation, interest rate, etc.) on the total factor energy efficiency (TFEE) of countries.

1.4 Research Questions

The study seeks to answer the following questions:

1. What RTS property underlines the energy sector of countries?
2. What is the level of energy efficiency of the countries?
3. What are the statistically significant differences in the distribution of energy efficiency scores of countries with and without the incorporation of environmental factors?
4. Has there been a change in overall productivity over the study period with and without the environmental factors?
5. What is the efficiency of the countries based on continental groupings?
6. What are the effects of economic factors on the energy efficiency of countries?

1.5 Research Scope and Limitations

Although this study contributes to academic research, practice and policy, it is not devoid of some limitations regarding method, data and time, although the study is very significant in explaining the environmental energy efficiency of countries. First, the initial aim of the study was to consider all countries in the world and to cover recent trends. This was made impossible due to data unavailability. However, the chosen sample size coupled with the chosen study period of 15 years (2000-2014) provide adequate data points good enough to make a generalization on all countries.

Methodologically, the study uses DEA, which is outlying distribution-free and hence, may statistically be constrained due to the presence of outliers and sampling variations that may bias the results. This issue is dealt with via bootstrapping or resampling techniques.

Second, the study combines all energy sources into one measure of energy consumption to enable us find the Total factor efficiencies, although it would have been best to disaggregate the energy consumed into various source so as to identify the impact of each energy source on the overall efficiency score.

1.6 Thesis structure

The study consists of six chapters. Chapter one describes the background, research problem, research objectives and questions, contributions of the study and limitations of the study. Chapter two presents the contextual setting for the study. An overview of the energy sector is presented in the subsequent sections. These expositions provide a fair idea of the energy sector, its activities, importance and other issues worth noting. Chapter three focuses on the review of existing relevant literature, theoretical and empirical. Chapter four discusses the methodology used. This will also consist of definitions of data and variables and how the collected data is analyzed to achieve results. Chapter five presents the results obtained from carrying out the appropriate analysis, with detailed discussions of the results. Chapter six concludes the research by summarizing the findings and recommending policies based on findings. Areas for further research shall also be pointed out in the concluding chapter.

CHAPTER TWO

CONTEXT OF THE STUDY

2.0 Introduction

This chapter presents the contextual setting for the study. An overview of the energy sector is presented in the subsequent sections. A synopsis of the sector is presented first, followed by the environmental impact of the sector. These expositions provide a fair idea of the energy sector, its activities, importance and other issues worth noting.

2.1 ENERGY

Energy is the power we use for transportation, for heat and light in our homes and for the manufacture of all kinds of products. Globally, several economies are making use of diverse energy sources in satisfying their energy needs in various sectors of their economy (domestic, industry, agriculture, education, health, service and so on. There are two sources of energy: renewable and nonrenewable energy.

2.1.1 Nonrenewable Sources of Energy

Nonrenewable energy covers energy sources that contain high levels of carbon emissions (petroleum or coal). The utilization of these sources in the generation of energy results in negative environmental impacts due to the emission of greenhouse gases, as it may contribute to acid rain and global warming (Dincer, 2000). Due to the negative externalities created by the utilization of traditional energy sources- fossil fuels on global climate. For the reduction and mitigation of current and future threats posed by fossil-fuel consumption to the global climate to be achieved, several alternatives have been recommended by various scientific institutions and essential stakeholders (COM, 2000; IPCC, 2014; Mallon, 2006). Consumption of fossil energy in developed countries has increased rapidly, and is now decreasing as a result of their transition towards energy sources with minimal carbon emissions. But, developing countries consumption of fossil energy is still increasing due to increasing incomes (triggering an increase in per capita energy) and populations (Ritchie & Roser, 2018). One route to ensure the reduction in greenhouse gases specifically carbon dioxide is the broadening and adoption of alternative sources of energy that emits minimal (debatable zero) greenhouse gases. These alternative sources of energy are either directly or indirectly from the sun (wind energy, bioenergy, and hydropower) and energy not from solar power e.g. geothermal and tidal (Boyle, 2004). The sphere of green energy technology comprises of a continuous discovery of environmentally friendly techniques and approaches for the generation of non-traditional energy such as solar energy to administrative instruments that aid in the regulation of greenhouse gas emissions (Show, 2010).

2.1.2 Renewable Sources of Energy

Renewable energy is the type of energy that is derived from natural resources such as sunlight, tides, rain, wind, geothermal heat and waves that can be replenished and have minimal impact on the environment as less pollution is generated in its usage (Ellabban, Abu-Rub, & Blaabjerg, 2014). Renewable energy technology adoption must be sustainable and efficient, meaning the needs that are required to be satisfied should not pose a threat on the capability of subsequent generations to satisfy their own needs and it should be cost-effective without comprising quality and quantity. This can be achieved through an integrated principle i.e. social, economic and environmental aspects of green technology should be considered (Camagni, Capello, & Nijkamp, 1998). The existence of renewable energy resource cannot be underestimated because there are numerous of them, particularly solar, biomass and wind (Jacobsson & Bergek, 2004). The rapid increase in renewable energy adoption is leading to significant climate change mitigation, energy security and socioeconomic benefits (IEA., 2012, 2016). For the modernization and upgrading of electricity systems globally, green energy is now the front-runner alternative. In 2015, solar and wind energy attracted 90% investments in renewable energy which facilitated their competitiveness with fossil energy due to declining costs in recent years. For every five units of energy consumed, one unit is generated from renewable energy source (IRENA, 2017). Below are some of the common renewable energy technology sources.

2.1.3 Solar Energy

The advancement in technology and decreasing costs are influencing renewable energy adoption globally, with the front-runner being the power sector in terms of the adoption. Solar photovoltaic technology exhibits this more. In 2015, global solar photovoltaic installations experienced a rapid increase from 40 gigawatts in 2010 to 219 gigawatts, this was as a result of an estimated 20% of newly installed electricity generation (IRENA, 2016).

Solar energy technologies have not been popular in the African continent in terms of the generation of electricity although sunshine is an abundant resource on the continent. Africa as a continent is distinctly endowed with the potential of solar energy. Of which majority of the continent experiences energy generating sun rays more than 45 weeks per year with irradiation magnitude of approximately 2000 kWh per square meter which is two times the level of irradiance of Germany (JRC, 2016). There is an approximated 50% market increment of solar energy technology adoption annually, this amount to at least 75 GWdc – approximating to more than 31,000 solar energy generating panels that are mounted every sixty minutes – increasing the world aggregate to a minimum of 303 GWdc. China emerges as the country that is leading in the exploration of solar energy with an estimated 85% additions with respect to other top countries. Yet upcoming markets across the globe are contributing appreciably to the world solar energy expansion, and majority identify solar Photovoltaic as a reliable and profitable source for improving efficient electric power generation and for the provision of equitable access to energy (Sawin et al., 2013).

About 30% of renewable energy was accounted for by solar photovoltaic in 2015 as an additional generation capacity globally. It also received about half ($149 billion) of the total green energy cash inflows ($301 billion) in the energy sector(BNEF, 2016). Furthermore, it is the major renewable energy employer, globally, creating an approximated 2.8 million employment opportunities in 2015 globally, in excess of 11% in 2014 (IRENA, 2016). An approximated 200 to 300 million tons reduction in carbon dioxide through solar photovoltaic energy generation per year and there can be a further reduction between 1 and 3 gigatons per year in 2030 (IRENA, 2016b). This reduction in carbon dioxide emissions represents the emissions of Poland at the high end (JRC, 2016).

2.1.4 Hydro Energy

Hydro energy is the biggest and the most commonly renewable energy source that is being exploited for the generation of power in most countries globally, it utilizes the gravitational force of running water to produce electricity. Electricity generated from hydro was estimated to account for 20% and 80% of the globe's electricity and of the overall electricity produced and supplied from renewable energy sources respectively (IRENA, 2012).

2.1.5 Bio Energy

Bio energy is a renewable energy source that is organically obtained from living substance or organisms, like effluent or sewage, lumber, and ethanol fuels. These sources of bioenergy are purposely built for the generation of electricity or the production of heat (Demirbaş, 2001). For the generation of electricity and heat, bioenergy is considered as a potential renewable energy source in most energy expansion developmental plans. In the European Union Renewable Energy Action Plan(s), each EU country made a 19%, 77% for green power and heat respectively will be obtained from bioenergy (ECN, 2011). According to the World Energy Outlook (IEA, 2010), 1379 TWh (4.6%) of electricity generated globally came from bioenergy and residue or waste and an approximated 1225 Mtoe for heat generation.

2.1.6 Wind Energy

Electricity generated from wind has remained very insubstantial when setting side by side with electricity generated from hydro, with only 190 MW in all of sub-Saharan Africa, even though the net present value of the factor cost of electricity from mainland wind technologies have decreased considerably in recently. The prospects of wind in Sub-Saharan Africa is approximated to be 1300 GW (Mandelli, 2014).

2.2 Impacts of Energy use on the Environment

Pollutants cause a lot of harm to the environment. Energy supply and use also comes with the release of certain emissions which causes some detriment to the environment amongst which are global warming, emission of radioactive substances, air pollution, acid rain, depletion of the ozone, and forest destruction.

2.2. 1 Acid rain

Combustion of fossil fuels usually produces pollutants such as SO2 and NO*x* which are carried over great distances through the atmosphere and deposited on the earth's ecosystems that are exceedingly vulnerable to damage from excessive acidity. To control acid rain deposition the necessary measures should be put in place to reduce the SO2 and NO*x*. Energy-related activities also serve as a major source of acid rain. For instance, 70% of SO2 emissions are accounted by the generation of electric power, residential heating and industrial energy use.

2.2.2 Global climate change

Greenhouse effect is generally a term used to describe the earth's surface being warm as a result of the role of the atmosphere. Even though other gases such as CH4, CFCs, and N2O which are generated by activities both at industrial and domestic level also contribute to a rise in the earth's temperature causing these greenhouse effects, CO2 is estimated to have the highest accounting for about 50% to these greenhouse effects. There is an increase in the surface temperature of the earth leading to a rise in sea level which is affecting the survival and activities of man in various ways including flooding of the coastal settlements, a displacement of fertile areas for agriculture toward higher latitudes which are infertile, and a decrease in the availability of fresh water for irrigation and other essential uses (Colonbo, 1992). Thus, CO2 which is released from fossil fuel combustion and methane emissions from increased in the activities of humans have all contributed to the greenhouse effect. Most scientists are of the view there is a cause and effect relationship between the greenhouse gas emissions and global warming.

Through the formation of some international institutes and agencies the developing and developed countries are striving to attain sustainable supply of energy sources through reduction in emissions of pollutant.

For example, International Kyoto Conference on climate change which was formed in December 1997 saw a list of 15 proposals to help eliminate these emissions.

CHAPTER THREE

LITERATURE REVIEW

3.0 Introduction

This chapter presents a review of relevant theoretical and empirical literature on environmental energy efficiency. The theoretical review presents the theoretical background relating to environmental efficiency. The second part reviews empirical studies on energy efficiency.

3.1 Theoretical review

There exist a number of theories that explain the concept of energy efficiency. The section begins with a theoretical review on the concept of energy efficiency and its measures, outlines some environmental theories.

3.1.1 Energy Efficiency

Energy efficiency has different meanings, hence is defined differently by a lot scholars making it a relative concept, it can be defined as the use of less energy to produce the same amount of some useful output (Ang, 2006). Amid the 1970's, energy efficiency got much concentration because of the 1973 world oil crisis (Honma, & Hu, 2009; Zhou, & Poh, 2008).With the costs of energy increasing considerably within this period, policymakers and economies became intrigued by how viably energy resources were being utilized and to guarantee the conceivable greatest measure of output were delivered with the given level of energy inputs (Ang, 2006). In any economic production activity energy and other resources are usually combined to produce an output which can be good output (GDP) or a bad output (CO2, SO2) hence a total-factor efficiency evaluation model is needed to able to combine all of these resources. In order to give a more realistic efficiency score, the environmental efficiency should not be ignored when assessing energy efficiency where bad emissions of pollutants are used as by-products.

The idea of energy efficiency has therefore turned out to be vital to the energy policy of different economies (Ang, 2006; Bosseboeuf, Chateau, & Lapillonne, 1997; Zhou, & Poh, 2008; Patterson, 1996). This thoughtfulness regarding energy efficiency was further underscored in the late 1980's with developing worries of global warming which is caused by fossil fuel combustion (Ang, 2006; Bosseboeuf et al., 1997; Chang, & Hu, 2010; Li, Crook, & Andreeva, 2014; Zhang et al., 2011). The International Energy Agency (IEA) in 2014 distinguished that the generation and utilization of energy adds to 66% of the world's CO2 emissions (IEA, 2015). In this sense, energy efficiency is viewed as the principle channel through which economies can accomplish emissions targets set by the Kyoto Protocol (Ang, 2006; S. Honma, & Hu, J.-L., 2009). Energy efficiency is likewise observed as a method for accomplishing industrial competitiveness and energy security (Singh, 2016). Nonetheless, regardless of all the expressed reasons and emphasis on energy efficiency, it has been hard to turn out with a solitary definition for what precisely energy efficiency is (Patterson, 1996), due to its applications in various fields such as engineering, environmental studies and economic studies. Due to its applications in these diverse fields, the definition tends to differ based on the field it is been applied in. That is what energy efficiency might mean to the economist may be different from what it might mean to an environmentalist, an engineer. For instance, energy efficiency to the environmentalist will mean a reduction in the amount of GHG emissions, whilst to the economist might place more emphasis on increasing some economic output.

Traditionally, energy efficiency can be defined as the use of less energy to produce the same amount of some useful output (Ang, 2006). Note however that in defining *energy efficiency*, care must be taken to differentiate it from *energy conservation*. Energy conservation implies reducing energy usage by deliberately foregoing some energy services (Herring, 1996). Examples include turning off air-conditions and relying on ventilation through open windows and doors to preserve prepaid energy units. Mathematically, Patterson (1996) defines energy efficiency as the ratio of some useful output to a process to the energy input into the process. That is:

$$\frac{Useful\ Output}{Energy\ Input}$$

Given the multi dimensionality and importance of energy efficiency, various indicators have been developed for its measurement. Patterson (1996) identifies that these indicators fall into four main groups;

Thermodynamic indicators, Physical-Thermodynamic indicators, Economic-Thermodynamic indicators (monetary based indicators) and Economic indicators.

Thermodynamic indicators: This is measured at the device level and is purely in thermodynamic terms. For instance the degree of heat provided by a thermostat or the degree of cooling provided by an air conditioner (Ang, 2006).

Physical-Thermodynamic indicators: The output produced is measured in some physical units such as tones of passenger miles, amount of physical goods produced (Bosseboeuf et al., 1997; Patterson, 1996).

Economic-Thermodynamic indicators (monetary based indicators): This involves the measurement of energy efficiency where the output is measured in monetary terms with the energy input measured in thermodynamic terms (Bosseboeuf et al., 1997)

Economic indicators: With these indicators both the energy input and useful output are transformed into some monetary measures.

The measure of energy efficiency adopted in this study can be classified under the monetary based indicators with GDP measured in monetary terms and energy measured in kg of oil equivalent per capita.

Energy efficiency indicators are mainly classified into simple single factor indices and composite indices (Apergis et al., 2015). Traditional single factor indicators include the energy-GDP ratio (energy intensity index) and the GDP-energy ratio (energy productivity) and are based on a relative measure of output to energy inputs only (Apergis et al., 2015; Chang & Hu, 2010; Li & Hu, 2012). This has been the basis for criticism of the single factor indices. It is argued that per their definition and not considering other inputs of production such as capital and labor, the single factor indices imply that all attainable output is as a result of energy consumption alone (Zhang et al., 2011). However, energy alone cannot produce any output and hence must be combined with other inputs (Zhang et al., 2011). Moreover, these measures tend to overestimate energy efficiency due to the substitution effects between inputs and fail to measure the underlying technical efficiency (Chang & Hu, 2010; Hu & Wang, 2006). Therefore estimating energy efficiency using the partial factor indicators presents misleading results (Honma & Hu, 2009; Hu & Kao, 2007; Hu & Wang, 2006; Larson, 2006). The best approach then is to measure energy efficiency within a total factor framework, which considers other inputs of production (Hu & Wang, 2006). To this effect, Hu and

Wang proposed the so-called TFEE while considering labor and capital as additional inputs in the production process. This measure of energy efficiency does exactly what the partial factors fail to consider. That is, it takes into consideration the complementarity or substitutability of inputs, measures the underlying technical efficiency and has the possibility to disaggregate the energy inputs. Given its advantages over the single factor indices, the current study adopts the TFEE.

3.1.2 Theories of Environmental efficiency

This section provides a discussion of the theories that underpin the study. The theories provide an insight for understanding why or how some of companies withhold certain information about their environmental efficiency in their corporate annual reports (Clarkson, Li, Richardson, & Vasvari, 2008; Deegan, 2006; Hahn, 2015; Huang, 2010; O'Donovan, 2002; Sullivan, 2012).

3.1.3 Legitimacy Theory

The theory asserts that for a firm to exist, its values must meet the expectations of the society within which it operates (Cho, Guidry, Hageman, & Patten, 2012; Magness, 2006; Shehata, 2014). Hence there is a social contract between the society and the companies based on this theory and therefore the firms influence the social system and are also influenced by the same social system. This theory explains what kind of information firms disclose, why such disclosures are made, and how these disclosures are made (Magness, 2006). Most companies in order to legitimize their activities report on their environmentally-related activities (Cho, 2009; Kamal, 2013). Unveiling environmental- related activities in their corporate annual report serve as a means to legitimize these companies (Lightstone, 2008).

Companies whose activities negatively impact the environment tend to face more of such pressures and its associated risks, hence the theory posit that such companies tend to disclose more environmental information as a means of offsetting the public pressures that arise from their poor environmental performance. It is therefore seen that companies whose legitimacy is undermined and confronted more by public pressure tend to disclose more environmentally-related issues as a way to mitigate their legitimacy crisis.

Van Staden, &Villiers, (2006) in their study using the annual reports of some selected companies in South Africa revealed that there is a negative relationship between the level of information unveiled on the environmentally related issues of a firm and its environmental performance. Similarly, Cho, & Patten, (2007) study found a negative relationship between the level of environmental disclosures and environmental performance. They therefore concluded that firms unveil information on their environmental related issues as tools of legitimacy.

3.1.4 Signaling Theory

The signaling theory is utilized to clarify the willful unveiling of certain information. As an economics-based voluntary disclosure theory (Healy, 2001), the signaling theory asserts that in instances where there exists an asymmetric distribution of information, company managers make willfully discloses certain information about their companies mainly to separate themselves from their companions when the benefits of such exposures far exceed the related costs.

Researchers have used the signaling theory, not only as an explanation to the willful unveiling of financial information, but also to explain the rationale for the disclosure of non-financial information, including environmental information, voluntarily (Bewley, 2000; Clarkson, Li, Richardson, & Vasvari, 2008). These researchers posit that companies whose activities have less impact on the environmental tend to disclose more environmental information as a way of revealing their nature as better performers (Clarkson, Fang, Li, & Richardson, 2013; C. M. de Villiers, 2016; Plumlee, 2015). The theory tends to suggest that firms would not choose to be "responsive actors", but rather would willfully disclose information on their environmentally related activities as an instrument to communicate, create and enhance their reputations (Hasseldine, 2005). This is further echoed by Clarkson, Li, Richardson, & Vasvari, (2008) who asserts that companies that are environmentally efficient will more likely than not provide information on their environmental related activities, to their stakeholders to signal them of their accomplishment. Thus, for environmental efficient firms, more environmentally related information will be made to signal their type. Such information is seen as a way of signaling stakeholders of their positive environmental efficiency. This provides a competitive edge for such firms and enhances their reputation in the society (Lys, 2015; Mahoney, 2013).

Al-Tuwaijri (2004), in their measure of environmental performance, used the ratio of toxic waste recycled to total toxic waste generated and found a positive relationship between environmental performance and the disclosure of environmental related information on their company. The study concluded that firms that are environmental efficient disclose willfully their environmental related issues of their company as a way of informing key stakeholders of their strategies and achievements. When environmental efficiency is better, the perceived benefits of unveiling information on their environmental related issues are seen to be higher and the perceived related cost such as risk of legal exposure is lower; thus, firms are motivated to disclose more environmentally-related issues (Aerts, 2009). The conclusion drawn is consistent with that of Clarkson, Li, Richardson, & Vasvari, (2008).

Cho et al. (2010) in their study revealed that there is a positive relationship between environmental efficiency and the level of information disclosed about their environmental related issues. A cross-sectional sample of 190 US firms in the 2002 fiscal year was used to determine the amount of information disclosed in their annual reports.

3.1.5 Pollution Haven Pressure

The pollution haven Hypothesis refers to the shifting of environmental effect of emission from one country to the other, either by physically relocating the firm or outsourcing parts of its production lines (Dinda, 2004). This pollution haven pressure is the policy aspect of comparative advantage (De Melo, 2010). If consumption in developed countries does not change proportionately in response to the structural change in production, then a situation of displacement of dirty productions may occur. In other words, if developed countries would want to maintain their pattern of consumption; then dirty industries may tend to migrate from the developed countries whose environmental regulations have grown tighter as predicted by pollution haven pressure to weaker regulatory countries which are mostly developing and emerging economies (Copeland, 1995). This supposes that poorer countries may tend to be net exporters of pollution intensive goods while the richer countries become net importer. In essence, pollution on the global scale may not necessarily fall since poor countries specialize in the production of dirty and resource-intensive goods while the higher income countries concentrate on “cleaner” productions (Stern, Common, & Barbier, 1996).

However, substantial amount of empirical studies that have investigated the pollution haven hypothesis failed to find evidence to support the claim (Cole & Elliot, 2003; Grossman & Krueger, 1993), since firms in highly regulated countries do not relocate systematically due to the pollution haven pressure as hypothesized. This could be attributed to the fact that pollution intensive firms are subjected to pressures from both pollution haven and factor endowment effect (Antweiler, 2001). Particularly because dirty industries are more capital intensive -characteristically physical capital intensive (Cole, & Elliott, 2002) and relatively human capital intensive (Cole, Elliot, & Shimamoto, 2003) and may be more competitive where there is capital abundance, hence the two pressures may cancel each other out (Antweiler, 2001; Cole 2003b; Cole, & Elliott, 2005).

Ederington, Levinson, & Minier, (2005), attributed the lack of compelling evidence to support the pollution haven hypothesis to three reasons. First is that, the chunk of international trade often occurs amongst developed countries whose regulations are similarly stringent, as such aggregate trade pattern analysis is unlikely to reveal the trade-environmental regulation nexus that occur between developed and less developed economies. Secondly, the cost of environment is minimal or forms a small portion of the total cost of production of polluting firms. Hence, the pressure for the firms to relocate is virtually negligible but there may be some small section of industries that may find it costly and may fall into the pressure of pollution haven. Their final argument was that, industries have different degrees of flexibility; some are more footloose than others. As such, those that have huge fixed plant costs, high transport costs of mobility or enjoy some benefits from economies agglomeration are less likely to relocate physically. Thus, previous studies that mixed analysis of relatively footloose and immobile industries may fail to detect the pollution haven.

Ederington, & Minier, (2003) provided proof of all three argument in the US using industry-level data from 1978 to1992. In their study, air quality in the US was found to be greatly influenced by changing technology rather than the shifting of dirty industrial activities abroad (Levinson, 2009). Theoretically studying aspects of immobile industries and the level of economies agglomeration, Zeng (2009), demonstrated how agglomeration can cancel out pollution haven especially if there exists just a minor difference in stringency of regulations between the developed and developing countries.

Cole, Elliot, & Shimamoto, (2003), attributed to the composition of determinants of US specialization, which requires more physical and highly skilled human capital. Moreover, industrial processes that use highly skilled labour tend to be pollution intensive processes (Cole, Elliot, & Shimamoto, 2003).

The correlation between physical capital intensity seems to be well grounded. What is yet to be recognized by environmental literature is the human capital requirement of the pollution intensive sectors. The general assumption of Cole, Elliot, & Shimamoto, (2003) is that industries that uses highly skilled labour tend to be pollution intensive and that cleaner sectors tend to use relatively low skilled labour. If this claim is true, then Africa's environment should be adjudged one of the cleanest since its production process rely heavily on low-skilled employees. This however, does not seem to be the case. Partly because of the loose environmental regulations across African countries which resent a comparative advantage in pollution intensive sector of the region (IPCC, 2001). This follows that whether a country will be subjected to the pollution haven pressure or not depends on the environmental regulations.

3.1.6 Environmental Regulation

The environmental regulations could either be formal or informal (Dinda, 2004). Formal regulation is where countries sign treaties to enforce environmental regulations which are passed on to state institutions and other regulatory bodies to carry out. However, when these formal regulations fail, societies through informal channels and other market forces put across measures to reduce the environmental pollution. Unless environmental regulations are stringent, pollution would increase (Hettige, 2000). If this claim is true, then the structural change in production signified by the composition effect may result in pollution as dirty firms relocate physically to economies with less stringent regulations or are displaced simply by similar dirty firms in environmental abundant countries (Ekins, 1997; Rothman, 1998; Stern, Common & Barbier, 1996). It is important that environmental institutions and policies advance in response to economic growth. In an open economic model with two-commodities, Siebert (1977) (as cited in (Xing, 1996) conducted a comparative static analysis for the relative prices of commodities. The model used one non-tradable resources as input and pollution modeled as a by-product of production. The relative prices of commodities were modeled as a function of environmental pollutants. Siebert's model revealed that marginal product of an industry is not the only determinant of relative commodity prices, rather damages sustain socially, pollution tendency of industries and unit effluent charges should be added. As such industries should be made to absorb the social damage through the payment of effluent charges. Seibert suggested that environmental regulations should be enforced by the agencies in charge of environmental protection. In some cases, technology standard are more preferred to effluent fees by the environmental regulations, Carraro (1992) examine the effect of those environmental regulations that require new technology standards. Their model assumed capital goods and technology are not traded. It also assumes that all countries have identical technology and that home country upon engaging in free trade imposes mandatory technology standards to curb pollutions. This investment in new technology raises the marginal cost of the goods produced and subsequently reduce profit margin. Using perfect competition, Cournot, oligopoly and Bertrand oligopoly conditions, Carraro (1992), analyzed how profits are affected by this emission control policy. They argue that, the new technology requirement by environmental regulations coupled with the competition faced by domestic industry in world trade will thwart competitiveness of domestic industry, leading to profit losses. They suggested that government subsidies for the loss of competitiveness to keep domestic industry in business or risk them relocating to other countries. It is clear from these theoretical arguments that there are efficiency losses and externalities from trade and government has a role to play to reduce pollution.

3.2 Empirical review

3.2.1 Environmental energy efficiency

Data envelopment analysis (DEA) has of late been broadly connected to considering the efficiency related to both energy and environmental at the macro-economy level, as it furnishes a proper technique to manage multiple inputs and output sources in determining relative efficiency.

The concept of efficiency is defined as the ratio of the actual amount of some output that can be produced from a given unit of input(s) to the actual amount produced. Therefore, an entity that is able to use less amount of energy inputs to produce the same amount of "useful outputs" is said to be energy efficient (Patterson, 1996). Over the past 10 years, the development of energy efficiency indicators have attracted some interests (Ang, 2006; Murray G. Patterson, 1996). Broadly, energy efficiency is measured within two frameworks: the single factor and total factor frameworks (Hu

& Wang, 2006; Patterson, 1996). The single factor measure of energy efficiency involves measuring energy efficiency using either the energy intensity measure or the energy productivity measure (Patterson, 1996). The energy intensity measure is where energy efficiency is measured as a ratio of energy inputs to outputs while in the energy productivity measure, the reciprocal of the energy intensity measure, is defined as the ratio of an economic output to energy inputs (Patterson, 1996). Hu and Wang (2006) and Hu and Kao (2007) developed what is known as the total factor framework for energy efficiency measurements which they called TFEE. This index was developed within the DEA methodology by including other input measures-labor and capital.

For instance, the study by Wu et al. (2018) on 28 APEC economies revealed that most countries exhibited higher economic efficiency than environmental efficiency, in terms of energy use efficiency Australia, Brunei, Hong Kong, and Singapore were seen as efficient countries throughout the whole five year period from 2006 to 2010; with respect to CO2 emission efficiency, Brunei, Hong Kong, and Singapore were recognized as proficient nations for the five sequential years from 2006 to 2010. In addition, both energy use efficiency and CO2 emission efficiency were found to be significantly related to the EEE value ($p < 0.01$).

A network DEA model was proposed by Yan & Qi, (2017) which can deal with negative externalities, and they used it for decomposition of the profit inefficiency in the biomass-agriculture circular system.

Guo, Qi, Zhou, and Li (2018) utilized a total factor framework to assess the coal utilization efficiency of six sub-businesses in China in 2015. The outcomes demonstrated that of the six concentrated sub- businesses studied, two showed both economic and environmental efficiency. China ought to hence give more consideration to the perfect use of coal.

Song, Zhang, Liu, & Fisher, (2013) analyzed the energy efficiency of BRICS countries using bootstrap DEA. Although they did not include CO2 emissions in their DEA analysis, they developed the relationship between energy consumption and CO2 emissions separately in their paper. On the other hand, Gómez-Calvet et al., 2014 and Zhou, (2008) included CO2 emissions in their energy efficiency analysis.

Several environmental DEA technologies were developed by Gómez-Calvet et al., (2014) and Zhou, & Poh, (2008) and used to measure the carbon dioxide emission performance of eight world regions but the model omitted other non-energy inputs and just dealt with energy input, desirable and undesirable outputs.

Yeh, Chen, and Lai (2010) utilized the traditional BCC DEA model that treated bad outputs following Seiford (2002) approach which increases the good outputs and decreases the bad outputs at the same time to determine the efficiency of Chinese terrain and Taiwan.

Although developed within the nonparametric DEA framework, the TFEE indicator has also been employed within the parametric framework of SFA. For example Zhou, Ang, and Zhou (2012) proposed a parametric framework for estimating energy efficiency by defining an index based on the Shephard distance function using SFA. The study applied the index to measure economy-wide energy efficiency of 21 OECD countries and compared the results with that of the non-parametric variable returns to scale (VRS) and constant returns to scale (CRS) DEA models. S. Honma and Hu (2014b) extended the cross-sectional SFA model of Zhou et al. (2012) using panel data to measure the total factor energy efficiency of 47 Japanese regions, comparing the TFEE from SFA to that of an input-oriented VRS DEA model, and simultaneously estimating the determinants of inefficiency. Their results show a high correlation (80%) between the SFA TFEE scores and the DEA TFEE score. Taking account for possible technology heterogeneities, Lin and Du (2013) and

Lin and Du (2014) also use SFA to measure energy efficiency in China. Lin and Du (2014) proposed a latent class stochastic frontier approach to measuring energy efficiency and applied it to 30 Chinese provinces. In an industry level analysis, Lin and Wang (2014) apply SFA to analyze TFEE of China's iron and steel industry, concluding that energy efficiency in China's iron and steel industry improved within the study period. Hu (2014) used SFA to measure plant level energy efficiency of 150 plants in the Chinese energy sector, while controlling for the substitution effects on the effects of energy use efficiency, which is normally ignored when estimating energy efficiency in terms of allocating efficiency.

Although SFA provides an alternate approach to estimating energy efficiency and is preferred by some researchers, this method has its own shortfalls. SFA requires a restrictive pre-specified production function, restrictive specification of the distribution of noise and inefficiency terms, has difficulty in handling multiple inputs and multiple outputs simultaneously, and fails to impose axiomatic properties of production theory such as convexity, concavity, free disposability and monotonicity despite having an advantage of modeling inefficiency and noise and having economic interpretations (Fried, Lovell, & Schmidt, 2008; Murillo-Zamorano, 2004; Murillo-Zamorano & Vega-Cervera, 2001; Zhao Xiaoli et al., 2014; Zhu, 2015). These problems are overcome by DEA.

Most recently, several DEA models was proposed by Bian (2010) to evaluate both the energy and environmental efficiency of 30 Chinese provinces. The study had some limitations, as the variation trend of the efficiency could not be seen due to the performance measured a single factor for a single year.

Based on the earlier work of Farrell (1957b), DEA is a linear programming methodology introduced by Charnes, Cooper, and Rhodes (1978) and extended by Banker, Charnes, and Cooper

(1984) used to evaluate the relative efficiencies of decision making units which employ similar inputs to produce similar outputs (Zhou et al., 2008). This methodology has been applied for benchmarking in various industries and sectors including the energy sector.

A lot of DEA based studies on energy efficiency and environmental efficiency in recent studies evaluate energy efficiency by using total factors and pollutant emissions.

A study conducted by Zhou et al. (2008), proposed several DEA models in which labor and energy consumption were used as two inputs with GDP as the only good output, and CO_2, sulphur oxides (SOx), nitrogen oxides (N2O), and carbon monoxide (CO) as the bad outputs to determine the environmental efficiency of 26 OECD countries from 1995 to 1997.

However since then, more country level and cross-country level studies have been undertaken including Adom, (2019); Apergis et al. (2015); Chang (2013); Chang and Hu (2010); Fang et al. (2013); Gómez-Calvet et al. (2014); (Halkos & Petrou, 2019); He et al. (2013); Honma and Hu (2009, 2014a); (Hsieh, Lu, et al., 2019; Hsieh, Lu , et al., (2019); Iftikhar et al., 2018; Kounetas & Zervopoulos, 2019); Li and Lin (2015); Li and Hu (2012); Lv, Hong, and Fang (2015); Mukherjee (2010); Ohene-Asare & Turkson, (2018); Ramanathan (2005); Song et al. (2013); Wang, Zeng, Wei, and Zhang (2012); Wu et al., 2018; Zhao Xiaoli et al. (2014) and Zhang et al. (2011) on energy efficiency and Chang and Hu (2010); He et al. (2013); Honma and Hu (2009); Ramanathan (2005); Wang, Zhou, and Zhou (2013); Wang, Feng, and Zhang (2014); Woo, Chung, Chun, Seo, and Hong (2015); Zou et al. (2013) and Lv et al. (2015) on productivity.

Zhou et al. (2008) showed a lot of DEA-type linear programming models to help measure energy efficiency of economies, the study used both energy and non-energy inputs as well as good and bad outputs. Again, weighted average energy utilization performance index, energy efficiency performance index and average energy utilization performance index which are the three energy efficiency indexes were presented. Their study had one limitation instead of assessing the total energy and environmental efficiency it only assessed energy efficiency independently.

Under any energy consumption performance study, one will mainly like to reduce the amount of all energy sources consumed as done in studies such as Honma and Hu (2009); Larson (2006) therefore employing non-fossil fuel energy consumption as one output to be maximized defeats the whole purpose of analyzing energy consumption performance. Moreover, the study failed to consider other traditional inputs of labor and capital, suggesting that fossil energy consumption alone can produce GDP, which is not the case (Hu & Wang, 2006). Second, the study failed to test for the RTS property of the technology, but rather chose to estimate both the CRS and VRS efficiencies and productivities. This is commendable, although it must be pointed out that using the traditional CCR and BCC models themselves present a disadvantage in the fact that they fail to consider the effects of non-radial slacks in their estimations (Tone, 2001).

Another cross-country study by Zhang et al. (2011), in analyzing the TFEE of developing countries used window analysis and Tobit model to analyze the relationship between energy efficiency and per-capita income. The study found Botswana to be among the most efficient countries selected, with Kenya being the worst performer with an average TFEE of 0.329 within the entire period. However, the results of the study could be disputed as it failed to consider the environmental effect of energy use (IEA, 2015; Li & Hu, 2012). Note also that the sample consisted of countries spread across the different world regions, hence using the window analysis, without recognizing the possible heterogeneities among the countries and regions could lead to biased energy efficiency estimates (Battese, Rao, & O'Donnell, 2004). The Tobit model estimation reported a U-shaped relation between TFEE and income per-capita. Yet, applying the second stage Tobit regression in efficiency assessment, as used in this and some other energy efficiency studies result in serial correlation and biases (Simar & Wilson, 2007, 2011, 2015). Again, the study failed to control for other factors that could affect TFEE, leading to misspecification error (Jeffrey Wooldridge, 2005).

Shi and Frees (2010) came up with three extended DEA models to assess the energy and environmental overall technical efficiency, pure technical efficiency, and scale efficiency of 28 regions in China in which the bad outputs were regarded as inputs and made to decline relatively to the energy inputs.

The DEA based models of Shi & Frees (2010) and Wang & Zhou (2011) in evaluating energy and environmental efficiency have weak discriminatory power. Their model assessed multi-period efficiency by simply determined the efficiencies of various regions in every year and afterward just looked at the performance of various years.

3.2.2 Energy Efficiency and Economic factors

There are some Economic factors which have an impact on determining efficiency but can neither be termed as inputs nor outputs. These variables also tend to be out of the control or influence of managers. Some of these factors are income, inflation, urbanization, energy prices. Empirical studies on the energy efficiency points to a positive relationship between energy efficiency and development (which is usually proxied as income per capita). Honma and Hu (2008) analyzed the TFEE of 47 Japanese prefectures and based on the graphical relationship between the two variables concluded on a U-shaped relationship, similar to the environmental Kuznets curve hypothesis. Xiaoli et al. (2014) used income per capita as a proxy for economic development in their study of the TFEE of Chinas provincial industrial sectors investigated the factors that affect TFEE using a Tobit model, with economic development considered as one of the explanatory variables and reported a positive relationship between TFEE and economic development. A common feature and limitation of these studies is that by using the Tobit model, they fail to recognize and solve the serial correlation problem of the independent variables as identified by Simar and Wilson (2007, 2011, 2015).Wei, Yagita, Inaba, and Sagisaka (2003) analyzed the impact of urbanization on energy consumption and CO_2 emissions in china and found a positive relationship between urbanization and CO_2.

CHAPTER FOUR

METHODOLOGY

4.0 Introduction

This chapter discusses the procedures, techniques and methods used to achieve the objectives of this study. The chapter explains the research design, sampling and sources of data, data collection procedures, estimation techniques as well as the various data analytical methods employed in the study.

4.1 Research Design

The quantitative approach is used to examine the collected data using statistical procedures and hypothesis testing. This approach allows us to generalize and replicate the findings of the study (John W Creswell, 2013). The approach has an advantage of limiting researcher bias (Creswell, 2012). Panel data methodology is employed in making statistical inferences thereby allowing for the study of multiple entities over a period of time.

4.2 Sampling and Sources of Data

The population of this study constitutes all continents, out of which a sample of 135 countries is selected over the period of 2000 to 2014 due to the lack of availability of data. For the first stage TFEE estimation, three inputs (capital, labor and energy consumption) are considered to produce four outputs, GDP as the desirable output and CO2, N2O and CH_4 as the undesirable outputs.

Data for labour, capital and real GDP is sourced from World Bank Indicators (WDI). Energy and CO2, NOX and CH_4 related data is also collected from the World Bank Indicators. Due to the non-availability of data for some countries for some years, this research relies on an unbalanced panel data.

4.3 Frontier Efficiency Analysis

The measurement of technical efficiency is based on the conceptual approach of Debreu (Debreu, 1951) and Koopmans (1951) as first implemented by Farrell (1957a). This approach was substantially extended by Charnes et al. (1978) who referred to the technique as Data Envelopment Analysis (DEA) under constant returns to scale and later by Banker et al. (1984) (BCC) to handle variable returns to scale. DEA is a nonparametric optimization approach to evaluating the relative efficiency of homogeneous decision making units (DMUs) that use multiple inputs to produce multiple outputs (Banker et al., 1984; Charnes et al., 1978). Using the minimum extrapolation principle based on linear programming techniques, DEA assesses the relative efficiency of homogeneous DMUs based on a constructed frontier (Thanassoulis, 2001). The DMUs on the frontier (the boundary of the technology set) are classified as the efficient ones whilst those DMUs in the interior of the technology set are labeled inefficient (Cook, Tone, & Zhu, 2014). The technique goes further to identify the sources of inefficiency for the dominated units and sets improvement targets as well as role models which can be emulated by these dominated DMUs (Avkiran, 1999). DEA is, therefore, referred to by a number of scholars as an important means for performance evaluation and benchmarking analysis (Cooper, Seiford, & Zhu, 2011; Fried et al., 2008).

DEA is favored in this study over other widely used techniques such as ratios and Stochastic Frontier Analysis (SFA) because of a number of reasons. First, unlike ratios and SFA, DEA has the ability to simultaneously deal with several inputs and several outputs (Banker et al., 1984; Charnes et al., 1978; Wanke, Barros, & Faria, 2015). Second, DEA unlike ratios is unit invariant; it is able to work with different units of measurements without the need for calibration (Lovell & Pastor, 1995; Pastor, 1996; Tone, 2001), hence it is possible to work with the number of employees, currency, number of barrels, number of bags etcetera all in the same study without the need to standardize all measurement to the same units. Third, whereas parametric analysis such as SFA requires the specification of functional forms and random error terms in order to estimate the efficiency of DMUs (Fried et al., 2008; Hartley & Medlock, 2012), DEA does not require any of such in its analysis which makes it preferable since these functions and errors are difficult to specify and could lead to erroneous conclusions if not appropriately specified. Finally, the technique is able to break down efficiency into many constituents such as technical, cost, revenue and profit efficiencies. This decomposition is very beneficial to managerial decision making as it helps to specifically identify the key sources of inefficiency in the oil industry.

In spite of the numerous benefits of DEA, the technique is not without some challenges. DEA has been criticized as being an outlier methodology, since the extreme data points usually form the frontier. Indeed, when there are outliers in the dataset, the frontier can be influenced by these outliers. Additionally, DEA is nonparametric in nature and sometimes researchers and management face the problem of economic interpretation. This shortcoming is however minimized by bootstrapping methods which help to make statistical deductions and also to handle sampling variations and serial correlation of DEA scores (Simar & Wilson, 1998; Simar & Wilson, 1999; Simar & Wilson, 2000). Another problem of DEA is its inability to differentiate between inefficiency and statistical noise. Due to its deterministic nature, DEA is not able to distinguish between stochastic noise and inefficiency and therefore attributes all deviations from the frontier to inefficiency (Odeck, 2007). This could lead to the overestimation of efficiency scores. However, the introduction of Stochastic DEA by Simar (2007) and Stochastic Nonparametric Envelopment of DEA by Kuosmanen and Kortelainen (2007) handles this problem.

4.4 Measuring TFEE with DEA

Two well-known indicators of energy efficiency used in policy analysis are the energy intensity and energy productivity indices (Zhang et al., 2011). However, these indices tend to overestimate energy efficiency since they consider energy as the single input for production, and hence attribute all production to energy. The best way then is to estimate energy efficiency in a total factor framework. Hu and Wang (2006) proposed the TFEE index, which has been employed by researchers for both country level and cross-country analysis. The TFEE is defined as:

$$TFEE = \frac{Target\ energy\, input_{(i,t)}}{Actual\ energy\, input_{(i,t)}} \qquad (1)$$

and: $$Target\ energy\, input \leq Actual\ energy\, input \qquad (1a)$$

$$0 < \text{TFEE} \leq 1$$

Where the target energy input is the target given by DEA after radial and non-radial slack adjustments have been made, and the actual energy input is the amount of energy input consumed. From equation (5a), the TFEE score always lies between 0 and 1, where a DMU is efficient and given the score of 1 if the target energy input equals the actual energy input and also the DMU is inefficient and given a score less than 1 if the target energy input is less than the actual energy input. The level of inefficiency is then defined by how large the difference between the target and the actual energy input levels is.

4.5 Formalizing the basic DEA model

To formalize the DEA model, let us assume there are N number of countries which use m nonnegative inputs associated with the production of s^g nonnegative good or desirable outputs and s^b nonnegative bad or undesirable outputs, the production possibility, T, can be defined as:

$$T = \{(x, y^g, y^b) : x \text{ can produce } (y^g, y^b)\}$$

Where: $x_i = (x_{i1},\ldots,x_{im})$ is a matrix for inputs, $y_i^g = (y_{i1}^g,\ldots, y_{is}^g)$ is a matrix for desirable outputs,

$y_i^b = (y_{i1}^b,\ldots, y_{is}^b)$ is a matrix for undesirable outputs and $i = 1,\ldots,N = 135$ for number of countries.

From the above, the radial efficiency measure can be estimated by solving the following linear programming problem:

$$\max h_0 = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}}$$

Subject to: (2)

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1$$

$$v_r, u_i \geq 0 \qquad j = 1,\ldots, n;$$

$$r = 1,\ldots, s; \qquad i = 1,\ldots, m$$

where j represents countries and runs to n, y_r and x_i represent output and input data respectively and v_r and u_i are input and output weights to be determined by the solution to this problem (Charnes et al., 1978). The above is a CRS model which can however be transformed into a VRS model by adding the additional constraint $\sum_{j=1}^{n} \lambda_j = 1$.

Equation (1) can be transformed into the following linear programming problem using the Charnes-Cooper transformation (Charnes & Cooper, 1962):

$$\theta^* = \underset{\lambda_j, \theta}{Min}\ \theta$$

subject to:

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{i0}; \qquad i = 1,2,\ldots, m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0}; \qquad r = 1,2,\ldots, s$$

$$\lambda_j \geq 0; \qquad j = 1,2,\ldots n \quad \theta \quad free \qquad (3)$$

4.6 The SBM-undesirable

DEA models fall under two main classifications: radial and non-radial. Radial models by their nature focus on the proportional reduction of all inputs (input efficiency) or increase in outputs (output efficiency) holding the other constant (Cook & Zhu, 2005; Cooper et al., 2011; Fried et al., 2008). The radial input (output)-oriented models only focus on ensuring input (output) efficiencies, consequently ignoring non-radial slacks in their estimation, a crucial shortcoming when undesirable outputs are considered (Apergis et al., 2015). The SBM, a variant of the DEA models, is a non-radial model that accounts for input excesses and output shortfalls in its estimation of efficiency, and hence has greater discriminatory power, an advantage it boasts over the radial models. Moreover, it is not affected by the statistics of the whole data set, is unit invariant and monotone decreasing with respect to input excesses and output shortfalls (Gómez-Calvet et al., 2014; Tone, 2001).

Therefore, the non-radial and non-oriented models are the best at capturing the whole measures of efficiency within the framework of undesirable outputs (Apergis et al., 2015). The objective of the non-radial non-oriented model with undesirable outputs is to simultaneously reduce inputs and undesirable outputs while increasing good outputs.

Following the technology T in (1) above, the non-oriented SBM model in the presence of undesirable outputs is formulated as:

$$\rho^* = \min \left[\frac{1 - \frac{1}{m} \sum_{i=1}^{m} \frac{s_i^-}{x_{io}}}{1 + \frac{1}{s_1 + s_2} \left(\sum_{r=1}^{S_1} \frac{s_r^g}{y_{r0}^g} + \sum_{r=1}^{S_2} \frac{s_r^b}{y_{r0}^b} \right)} \right]$$

subject to: (4)

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{io}; \qquad i = 1,2,\ldots, m,$$

$$\sum_{j=1}^{n} \lambda_j y^g{}_{rj} - s^g = y_{ro}; \qquad r = 1,2,\ldots, s,$$

$$\sum_{j=1}^{n} \lambda_j y^b{}_{rj} + s^b = y_{ro}; \qquad r = 1,2,\ldots, s,$$

$$\lambda_j \geq 0, (\forall j); \;\; s_i^- \geq 0, (\forall i); \;\; s_r^+ \geq 0, (\forall r), \quad j = 1,2,\ldots n$$

Where s_i^- and s^b represent excesses in input and undesirable outputs respectively, s^g represents shortfalls in desirable outputs and λ_j are intensity variables whose values will be determined by the optimal solution to the linear programming problem, equation (4). The objective function is monotone decreasing with respect to all s_i^-, s^g and s^b and $\rho*$ satisfies $0< \rho* \leq 1$. Note that the optimal solution satisfies $\lambda^*, s_i^{-*}, s^{g*}, s^{b*}$ such that a DMU is only efficient if $\rho*=1$, i.e. $s_i^{-*} = s^{g*} = s^{b*} = 0$. $\sum_{j=1}^{n} \lambda_j = 1$ could be added to the model above to transform it into VRS.

Using the Charnes-Cooper transformation (Charnes & Cooper, 1962), equation (3) can be linearized to the equivalent linear programming problem:

$$\tau* = \min\left(t - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{io}} \right)$$

subject to: (5)

$$t + \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^g}{y_{r0}^g} + \sum_{r=1}^{s_2}\frac{s_r^b}{y_{r0}^b} \right)$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{io}t; \qquad i = 1,2,\ldots, m,$$

$$\sum_{j=1}^{n} \lambda_j y^g{}_{rj} - s^g = y_{ro}t; \qquad r = 1,2,\ldots, s,$$

$$\sum_{j=1}^{n} \lambda_j y^b{}_{rj} + s^b = y_{ro}t; \qquad r = 1,2,\ldots, s,$$

$$\lambda_j \geq 0, (\forall j); \;\; s_i^- \geq 0, (\forall i); \;\; s_r^+ \geq 0, (\forall r), \text{t} > 0 \quad j = 1,2,\ldots n.$$

where the $\sum_{j=1}^{n} \lambda_j = 1$ constraint is added if VRS.

To illustrate the non-oriented SBM, consider the following data of seven hypothetical countries whose energy efficiencies are to be estimated.

Table 4.1: Hypothetical seven-firm data

DMU	ENERGY(INPUT)	GDP (OUTPUT)
A	10	8
B	40	18
C	10	4
D	50	10
E	30	5
F	30	18
G	50	18

The VRS non-oriented TFEE score for DMU C can be formulated as:

$$\varphi^* = \underset{\lambda, j, \varphi}{\mathrm{Max}} \ \varphi$$

$$\text{Energy constraint}: 10\lambda_1 + 40\lambda_2 + 10\lambda_3 + 50\lambda_4 + 30\lambda_5 + 30\lambda_6 + 50\lambda_7 \geq 10$$
$$\text{GDP constraint}: 8\lambda_1 + 18\lambda_2 + 4\lambda_3 + 10\lambda_4 + 5\lambda_5 + 18\lambda_6 + 18\lambda_7 \leq 4$$
$$\sum_{j=1}^{n} \lambda_j = 1$$
$$\lambda_j \geq 0$$

The results attained from solving the above problem with MaxDEA pro 7.0 ultra is shown in the table below.

Table 4.2: Comparison between radial and non-radial energy efficiency

DMU	Radial Efficiency Score	SBM Efficiency Score
A	1	1
B	1	0.75
C	1	0.5
D	0.320755	0.28
E	0.212121	0.208333
F	1	1
G	1	0.6

Table 4.2 compares the radial and non-radial non-oriented VRS efficiency scores for the DMU's whilst Figure 4.1 provides a graphical illustration. Note that the energy efficiency scores for the radial models are higher than that of the SBM model, where non-radial slacks exist. This is because the radial models do not incorporate non-radial slacks into their estimations, thereby overestimating the efficiencies of the DMU's. For example, under the radial VRS model, DMU C is energy efficient with a score of 1. On the contrary, it is total factor energy inefficient under the SBM, with a score of 0.5, due to an output slack of 4 units and hence has to further increase its GDP produced by 4 units (move to point A) to become energy efficient.

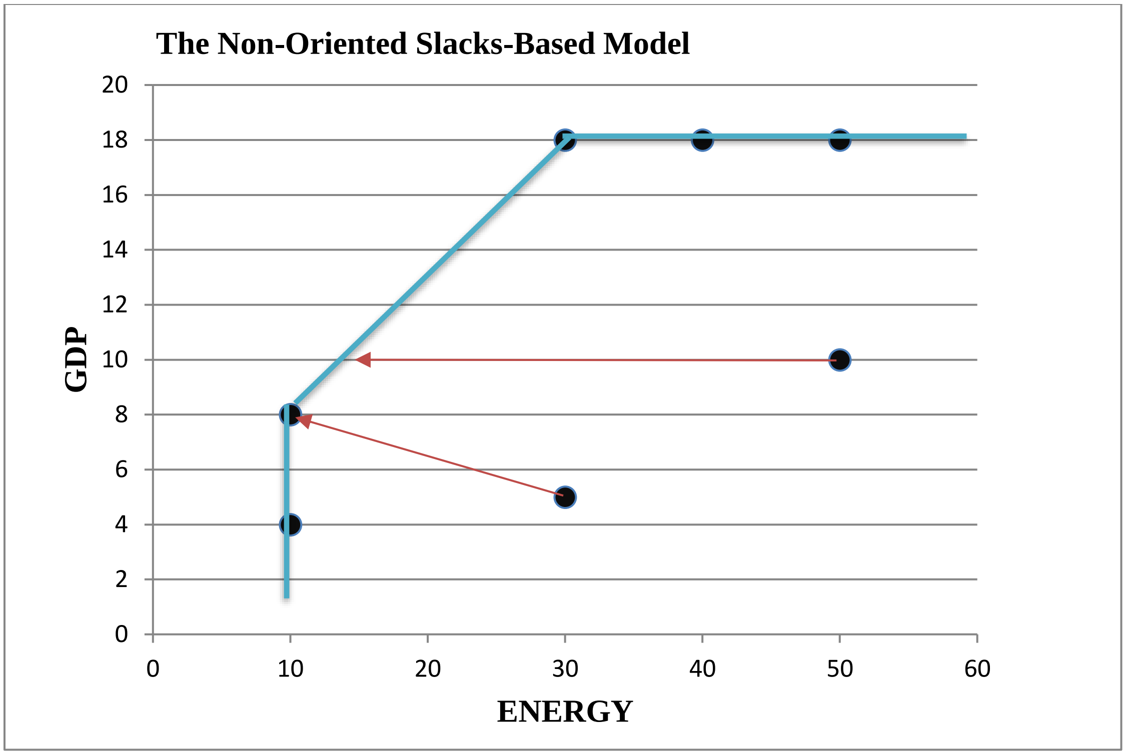


Figure 4.1: Graphical Comparison of Radial and Non-Radial Non-Oriented Models.

4.7 Meta-frontier Analysis

Since its inception, DEA has received several extensions. The metafrontier analysis is one of such extensions. Introduced by Battese & Rao (2002), enhanced by Battese et al. (2004) and further enhanced by O'Donnell, Rao, & Battese (2008), the metafrontier analysis helps to address some difficulties that accompany the assessment of efficiency of heterogeneous DMUs. While other methods such as ANOVA and second stage regression may be useful in providing some inferences on the impact of environmental variables, combining heterogeneous DMUs may distort the efficiency results (Assaf, Barros, & Josiassen, 2010). The metafrontier approach is therefore considered a more appropriate approach to employ in assessing the efficiency differences of groups. This is necessary as different groups could exhibit possible technology heterogeneity (Oh & Lee, 2010) originating from differences in infrastructure, resource endowment, firm-specific characteristics and other environmental and institutional factors (O'Donnell et al., 2008). Metafrontier analysis is based on the metaproduction function of Hayami (1969) and Hayami and Ruttan (1970). The meta-production function has some advantages but fails to account for inherent differences across groups (Battese et al., 2004). Therefore, the metafrontier approach overcomes this limitation allowing comparison across heterogeneous groups (Battese & Rao, 2002; O'Donnell, Rao, & Battese, 2008). Countries are in different groups based on their continental status and hence, are faced with different production capabilities such as the quality of physical and human capital, economic infrastructure and resource endowment. Therefore, the metafrontier also referred to as pooled or common frontier envelopes all other group frontiers and creates an overarching frontier for all observations (O'Donnell et al., 2008) to enable a fair comparison. It then measures two different efficiency scores for each DMU; efficiencies relative to the metafrontier (meta-efficiency) and relative to the group frontier (group efficiency) from which the technology gap ratio is then calculated.

Following Battese et al. (2004) and O'Donnell et al. (2008), given a nonnegative output vector *y* and input vector *x*, the meta-technology set is defined as:

$$T = \{(x, y) : x \geq 0; y \geq 0; x \text{ can be used to produce } y\} \tag{6}$$

The output-oriented technical efficiency of a DMU relative to the metafrontier (Meta efficiency) $(TE_0^M(x, y))$ based on a VRS assumption, can be defined as follows:

$$
\begin{aligned}
& TE_0^M(x,y) = Max\ \varnothing_o^* \\
& \quad s.t: \\
& \quad \sum_{k=1}^{K}\sum_{j=1}^{n} y_{rj}.\lambda_j \geq \varnothing y_{ro} \qquad \forall r = 1,\ldots,\ \text{s} \\
& \quad \sum_{k=1}^{K}\sum_{j=1}^{n} x_{ij}.\lambda_j \leq x_{io} \qquad \forall i = 1,\ldots,\ m \\
& \quad \sum_{k=1}^{K}\sum_{j=1}^{n} \lambda_j^t = 1 \qquad t = 1,\ldots,\ \text{T} \\
& \quad \sum_{k=1}^{K}\sum_{j=1}^{n} \lambda_j \geq 0 \qquad j = 1,\ldots,\ n
\end{aligned} \tag{7}
$$

It is worth noting that the output oriented Farrell meta efficiency score for inefficient DMUs is greater than 1 because it measures the ratio of expected output to actual output, for easy interpretation, the inverse of the score, the Shephard (1970) distance function is used to restrict the scores between zero and unity. A firm is said to be technically efficient if $\varnothing$ (that is, the reciprocal of the Farell score) is equal to unity and inefficient if $\varnothing$ is less than 1. In the model (2) above, y_{rj} represents the amount of the r^{th} output produced by the j^{th} DMU whereas x_{ij} represents the amount of the i^{th} input used by the j^{th} DMU. Where m is the number of inputs and s is the number of outputs for a set of n number of DMUs. Also, λ_j is the weight assigned to the j^{th} DMU, it shows the importance of DMUj in determining the efficiency of DMUo. $\varnothing$ is equivalent to TE_0^M which estimates the level of output augmentation needed by to make it efficient. $\sum_{k=1}^{K}\sum_{j=1}^{n} \lambda_j^t = 1$ is the VRS assumption, without which the model assumes CRS.

The efficiencies DMUs within the sub-groups in the meta-technology can be estimated. To do this the DMUs are now divided into K groups (where $K > 1$). The production technology defined in equation (1) can be redefined for the k^{th} group as:

$$T^k = \{(x, y) : x \geq 0; y \geq 0; \ x \text{ can be used by DMUs in group } k \text{ to produce } y \ \} \quad (8)$$

The VRS group-specific technical efficiency, $TE_0^k(x, y)$, can be then be formulated for a DMU relative to its group frontier as defined in equation (4):

$$\begin{aligned} & TE_0^k(x, y) = Max\ \varnothing_0^* \\ & s.t: \\ & \sum_{j=1}^{n} y^k{}_{rj}.\lambda_j^k \geq \varnothing y_{ro} && \forall r = 1\ ,...,\ \ s \\ & \sum_{j=1}^{n} x^k{}_{ij}.\lambda_j^k \leq .x_{io} && \forall i = 1\ ,...,\ \ m \\ & \sum_{j=1}^{n} \lambda_j^t = 1 && t\ = 1,...,\text{ T} \\ & \quad \lambda_j^k \geq 0 && j = 1\ ,...,\ \ n \end{aligned} \quad (9)$$

Where $\varnothing$, is the technical efficiency score relative to the group k's frontier.

From the meta efficiency and the group efficiency scores, the Technology Gap Ratio [TGR] (Battese et al., 2004) or Meta Technology Ratio [MTR] (C. J. O'Donnell et al., 2008) can be computed. The output-oriented technology gap ratio of a DMU in group k, $\text{TGR}_0^k(x, y)$, is the ratio of the DMU's Meta technical efficiency score to its group technical efficiency.

$$\mathrm{TGR}_0^k(x,y)/MTR_0^k(x,y)=\frac{TE_0^M(x,y)}{TE_0^k(x,y)} \tag{10}$$

The value of TGR ranges between zero and one and measures the deviation from the metafrontier (available technology irrespective of group) due to membership to a particular group *k*. In other words, it measures how distant, a particular DMU is from the metafrontier due to its membership to a particular group *k*. The meta technical efficiency of a firm can therefore, be decomposed as its technology gap ratio × its technical efficiency (C. O'Donnell, D. Rao, & G. Battese, 2008) as shown in equation (6) below:

$$TE_0^M(x,y)=\mathrm{TGR}_0^k(x,y)\times TE_0^k(x,y) \tag{11}$$

This decomposition is useful as it allows policy makers to better understand the source of any inefficiency and to properly target efficiency improvement programmes (Christopher O'Donnell et al., 2008).

4.8 Dynamic productivity estimation models

4.8.1 The Malmquist index

Since the seminal paper, DEA has received several extensions. The Malmquist Total Factor Productivity Index is one of such extensions. It was developed by Fare, Grosskopf, Lindgren, and Roos (1992), and is used to evaluate change in resource use over time. The ideas of Farrell's efficiency assessment and the earlier work of Caves, Christensen, and Diewert (1982) under the inspiration of (Malmquist, 1953) was merged by Fare et al. (1992). The index can be broken down into two different efficiencies, the efficiency change and technical change. The efficiency change or catching up effect, measures the change in technical efficiency of a DMU over time. Therefore, the changes in the productivity of the target DMU is attributable to management's efficient allocation of resources. The technical change or frontier shift component measures the effect of process or product innovation, (Färe, Grosskopf, & Lovell, 1994) that is, shifts in technology over time.

Assuming that for each time period *t: 1,…,T* and given that *N* countries at a time produces *m* non-negative outputs (denoted by $y \in \Re_t^m$) using *n* non-negative inputs (denoted by $x \in \Re_t^n$) the production possibility set (input-output combination set) can be defined as:

$$.\psi^t = \{(x^t, y^t) \in \Re_t^{m+n} \mid x^t can \text{ produce } y^t\} \tag{12}$$

The output oriented Farrell (1957) technical efficiency score, $\phi_0^t(x^{t+1}, y^{t+1})$, of a given firm (*xo*, *yo*) at time t relative to frontier t, under constant returns to scale can be arrived at through solving the linear programming problem below:

$$Max\phi_0^t(x^t, y^t)$$

$$\text{s.t} \tag{13}$$

$$\sum_{j=1}^{n} \lambda^t{}_j x^t{}_{ij} \le x^t{}_{io} \qquad \forall_i = 1,2,\ldots, n,$$

$$\sum_{j=1}^{n} \lambda_j^t y_{rj}^t \ge \varphi y^t{}_{r0} \qquad \forall_r = 1,2,\ldots, m,$$

$$\lambda_j^t \ge 0 \qquad \forall_j = 1,2,\ldots, N,$$

Where $\phi_0^t(x^t, y^t)$ is the output-oriented efficiency score that measures the proportional increment in the output of a DMU necessary to be efficient given the level of input. Note that if $\phi_0^t(x^t, y^t) \geq 1$ and only if $\phi_0^t(x^t, y^t) \in \psi$, also, if $\phi_0^t(x^t, y^t) = 1$ and only if (x^t, y^t) is on the frontier of the technology set (Fare et al., 1994). Note that the above model is formulated as CRS hence this third constraint $\sum_{j-1}^{N} \lambda = 1$ is usually added to transform it into a VRS model.

In order to define the Malmquist index there is the need to define efficiency scores with respect to two different time periods which would measure the maximum proportional change in outputs necessary to make (x^{t+1}, y^{t+1}) efficient in reference to technology in t. The result, $\phi_0^t(x^{t+1}, y^{t+1})$, may be less than 1 since (x^{t+1}, y^{t+1}) may not belong to Ψ^t. The proportional change in output necessary to make (x^{t+1}, y^{t+1}) efficient in relation to the technology in time t+1 can also be denoted as $\phi_0^{t+1}(x^{t+1}, y^{t+1})$. The Malmquist index according to Caves et al. (1982) with reference to the technology in time period t can, therefore, be defined as:

$$MPI^t = \frac{\phi^t(x^t, y^t)}{\phi^t(x^{t+1}, y^{t+1})} \tag{14}$$

A similar Malmquist index for the adjacent period can be defined in relation to the technology of time period t +1 as:

$$MPI^{t+1} = \frac{\phi^{t+1}(x^t, y^t)}{\phi^{t+1}(x^{t+1}, y^{t+1})}$$

In order to make sense of these two indices, Fare et al. (1992) proposed a geometric mean of the two indices as the means of avoiding arbitrary values of the productivity change index. This can be expressed as:

$$MPI^{t,t+1} = \left[\frac{\phi_0^t(x^t, y^t)}{\phi_0^t(x^{t+1}, y^{t+1})} \times \frac{\phi_0^{t+1}(x^t, y^t)}{\phi_0^{t+1}(x^{t+1}, y^{t+1})} \right]^{1/2} \tag{15}$$

Using the Fare et al. (1994) decomposition, the Malmquist index in equation (15) can be further disaggregated into efficiency change and technical change by rewriting it this way

$$MPI^{t,t+1} = \frac{\phi^{t}(x^{t}, y^{t})}{\phi^{t+1}(x^{t+1}, y^{t+1})} \times \left[\frac{\phi^{t+1}(x^{t+1}, y^{t+1})}{\phi^{t}(x^{t+1}, y^{t+1})} \times \frac{\phi^{t+1}(x^{t}, y^{t})}{\phi^{t}(x^{t}, y^{t})} \right]^{1/2}$$

EFFICIENCY CHANGE TECHNICAL CHANGE

Whereas the efficiency change component (EC) measures productivity change attributable to managerial acumen, the technical change (TC) component is as a result of changes in the total industry technology (Tortosa-Ausina, Grifell-Tatjé, Armero, & Conesa, 2008) depicting the impact of process or product innovation.

4.9 Bootstrapping the SBM

Since the SBM relies on the rudiments of DEA, it suffers from the problems of DEA. First, efficiency scores obtained by the application of the SBM measure lacks statistical underpinnings and cannot be used to properly make conclusions about the entire technology, since their values are estimated relative to an efficient frontier constructed by the chosen sample are sensitive to sampling variations (Simar & Wilson, 1998; Simar & Wilson, 1999; Simar & Wilson, 2000). Moreover, in selecting the input and output variables, one might select a variable that violates the assumption of isotonicity or omit a crucial variable which has implications for the efficiency estimates. Also, the efficiency of a particular DMU might be over or underestimated due to computational or measurement errors in the data inputting process. The above mentioned factors have the tendency of producing biased, estimates, hence lead to making flawed conclusions.

The bootstrap algorithms proposed by Simar and Wilson (1998, 1999, 2000) can help obtain statistical properties of these nonparametric estimators which could mimic the true underlining technology. The present study adopts the bootstrap algorithms to estimate TFEE, partly based on the views of Apergis et al. (2015) who recommend the need for efficient methodologies capable of estimating energy efficiency with no or little bias.

The basic idea of the bootstrap method is to make a numerical simulation of the original sample data, by sampling without replacement from the original sample data and to conduct DEA efficiency calculation to a large number of produced simulated samples so as to limit bias (Song et al., 2013). The efficiency bias is defined as:

$$Bias\ (\hat{\rho}_k) = E\ (\hat{\rho}_k) - (\hat{\rho}_k)$$

$$Bias\ (\hat{\rho}_k) = B^{-1} \sum_{b=1}^{B} (\hat{\rho}_k) - (\hat{\rho}_k) \tag{16}$$

The bias corrected SBM efficiency estimate can then be obtained as:

$$\tilde{\rho}_k = \hat{\rho}_k - Bias\ (\hat{\rho}_k) = 2\,\hat{\rho}_k - B^{-1} \sum_{b=1}^{B} (\hat{\rho}_k) \tag{17}$$

4.10 Returns to Scale (RTS) or scale elasticity in DEA

In estimating efficiency in DEA, one has to specify a type of RTS underlying the production technology. Specifying either CRS or VRS is a crucial question for any efficiency analysis since adopting a wrong technology assumption may distort results or lead to statistical inconsistencies (Simar & Wilson, 2002). To this effect, various authors have proposed various measures which however are criticized for their flaws (Simar & Wilson, 2002). More reliably, Simar and Wilson (2002) propose tests for RTS based on bootstrap algorithms. In doing so the following hypothesis are tested:

$H_0 = \Psi$ *is globally CRS*

$H_a = \Psi$ *is VRS*

To test the above hypothesis, the mean of ratios test by Simar and Wilson (2002) is adopted. The test statistic is defined as:

$$\hat{S} = n^{-1}\sum_{i=1}^{n}\left(\frac{D_n^{CRS}(x,y)}{D_n^{VRS}(x,y)}\right) \tag{18}$$

Where H_0 is rejected when $\hat{S}$ is significantly less than unity. To statistically test the hypothesis, since the distribution of the test statistic is unknown, bootstrapping procedures are used to generate p-values and critical values. Hence H_0 *is* rejected if the p-value is less or equal to the chosen significant level (Simar & Wilson, 2002). Alternatively, reject H_0 if the level of the test statistic is less than the critical value.

4.11 The Second Stage Estimation Procedure

One common practice in DEA efficiency studies has been to regress some environmental or contextual variables on the first stage efficiency scores via a two-stage process (Simar & Wilson, 2007). This is done following the idea that these variables have some impact on determining efficiency but can neither be termed as inputs nor outputs and hence cannot be included in the first stage estimation of the efficiency scores. These variables also tend to be out of the control or influence of managers.

The study employs panel data methodology to attain the set objective. Panel data methodology is used instead of cross-sectional data or time series because it exploits the merits of both time series and cross-section and also addresses the weakness of the latter techniques. It also help to better identify a model more than time series and cross section technique (Gujarati, 2009). Another advantage of panel data estimation is that it helps control for omitted variable error, insurer's specific effect and time specific effect (Wooldridge, 2010, 2015). According to Brooks (2019) the panel model is given by:

$$Y_{it} = \alpha + \beta X_{it} + \mu_{it} \tag{19}$$

i represents cross sectional dimension (insurer); t represents time series dimension (time); Y_{it} is the dependent variable; α is a constant term; β is $k \times 1$ vector of parameter of the independent variables; X_{it} is a $1 \times k$ is a vector of observations on the explanatory variables and μ_{it} is the error term.

In estimating the panel model, the study uses the ordinary least squares panel corrected standard error (OLS-PCSE) proposed by Beck and Katz (1995) because the assumption of homoscedasticity in panel models does not always hold. Also, using ordinary least squares (OLS) estimation techniques for panel model can be inefficient and biased due to the form of error terms in a panel model (Jeffrey M Wooldridge, 2015). Therefore, OLS-PCSE is more robust to heteroscedasticity and autocorrelation (Beck & Katz, 1995). Furthermore, for a more robust analysis, the panel model is estimated using random effects (RE) or fixed effects (FE) based on the Hausman test. These estimation techniques allow for variation across time and firms respectively which are not addressed by the OLS-PCSE. Also, due to the potential endogeneity in the panel model, the study further uses the two stage least squares (2SLS) and two-step system generalized methods of moments (GMM). Similar to previous works (Clark, Radić, & Sharipova, 2018; Koetter, Kolari,

& Spierdijk, 2008; Williams, 2012) the first and second lag of Lerner indices are used as instrumental variables in addressing the issue of endogeneity.

Second stage efficiency analyses is to address the factors that drive efficiency (McDonald, 2009). Tobit estimation was traditionally used in empirical papers for the second stage efficiency analyses (Bravo-Ureta et al., 2007; Ruggiero & Vitaliano, 1999; Vestergaard et al., 2002). However, the use of Tobit estimation for second stage efficiency analysis has been criticized because Tobit estimation technique is not able to address the heteroscedasticity errors in the second stage analysis using the efficiency scores (Arabmazar & Schmidt, 1982). Simar and Wilson (2007) also added that Tobit estimation failed to address the correlation between inputs and outputs used in estimating efficiency scores and the efficiency scores. Therefore, the authors argued that efficiency scores are not between the limits of 0 and 1 but truncated, hence proposed the truncated regression for second stage efficiency analyses. Finally, McDonald (2009) argued that efficiency scores are fractional data and not censored, making Tobit estimation technique biased. Despite the popularity of truncated regression used in empirical works (Barros et al., 2010; Du et al., 2018; Kenjegalieva et al., 2009; Lu et al., 2014; Luhnen, 2009), it has been criticized that the restrictive assumptions under truncated regression is not realistic under empirical setting (Banker et al., 2019). Therefore, OLS is argued to be more appropriate for second stage efficiency analyses because it is more robust than Tobit technique and truncated regression (Banker et al., 2019; Banker & Natarajan, 2008; Hoff, 2007; McDonald, 2009). Following, McDonald (2009), Banker et al. (2019) and Rajiv D Banker and Natarajan (2008), this study employs OLS in the second stage efficiency analyses. Similar to Alhassan and Ohene-Asare (2016), efficiency scores are logged in the second stage analysis and then estimated with OLS-PCSE to correct for autocorrelation and heteroscedasticity.

This is to address issue of bias. RE, FE, 2SLS and two- step system GMM are further used for robustness test.

4.11.1 Economic factors and TFEE

To test the relationship between economic factors and TFEE, the following specific model is adopted:

$$TFEE_{i,t} = \beta_0 + \beta_1 GNIPC_{i,t} + \beta_2 CAPLAB^2{}_{i,t} + \beta_3 INF_{i,t} + \beta_4 POPG_{i.,t} + \beta_5 INT_{i.,t} + \beta_6 EXCH + \beta_7 DEBT_{i.,t}$$
$$+ \beta_8 UNEM_{i,t} + \beta_9 AFR_{i.,t} + \beta_{10} ASIA_{i.,t} + \beta_{11} EUR_{i.,t} + \beta_{12} NAM_{i.,t} + \beta_{13} SAM_{i.,t} \alpha_i + \lambda_t + \varepsilon_{i,t} \tag{20}$$

Where *TFEE* is the TFEE score attained from bootstrapping the non-oriented SBM and *GNIPC* is the gross national income per capita, CAPLAB is a proxy for technology, *INF* is inflation. *POPG* is population growth, UNEM is unemployment rate, DEBT is the debt stock, INT is interest rate, EXCH is exchange, AFR, ASIA, EUR, NAM and SAM are dummies for the continents, Africa, Asia, Europe, North America and South America respectively and αi represents firm-specific fixed effects, λt captures time effects, $\varepsilon_{i,t}$ is the error term and the subscripts *i,t* represents a particular insurer *i*, at time *t*.

4.12 Input and Output Specification.

In selecting the input and output variables for this study, the study relies on an economic production function where three inputs are used to produce one desirable and three undesirable outputs. Consistent with reviewed literature, the study employs total energy consumption, capital stock, and labour as inputs and desirable GDP is accompanied by undesirables CO2, N2O, CH_4. These variables are presented in the table below with their units of measurements.

Table 4.3: Variable Definition and Description

Definition	Description
GDP	Real GDP measured in current US$
CO_2 (Undesirable)	CO_2 Emissions from the Consumption of Petroleum (thousand metric tons)
N2O (Undesirable)	Nitrous oxide emissions (thousand metric tons of CO2 equivalent)
CH_4(Undesirable)	Methane emissions (kt of CO2 equivalent)
Labour	Number of persons engaged (in millions)
Capital	Capital stock at current PPPs (in mil. 2005US$)
Energy	Total primary energy consumed (kg of oil equivalent per capita)

4.13 Chapter Summary

This chapter presented the methodology used to analyze the TFEE of the selected countries while incorporating environmental factors. It started by justifying the research design adopted in the study, then presented the sources of data and how the sample for the study was chosen. Subsequently, it presented the formalization of the basic DEA models, providing illustrations where necessary. Other methodology that were presented include the test for the underlying scale elasticity of the energy sector, and the second stage regression model.

CHAPTER FIVE

RESULTS, ANALYSIS AND DISCUSSIONS

5.0 Introduction

Chapter five presents the results from the analysis of data for the study and discussion of the results in order to answer the research questions and achieve the objectives of the study. It begins with the presentation of descriptive and summary statistics for the inputs and outputs. This is followed by the correlations between the inputs and outputs to test the isotonicity property of the data.

The scale elasticity test is then presented followed by the TFEE and bootstrapped TFEE results. The dynamic productivity of the countries is presented next, then the TFEE of the countries based on continental groupings is then presented following the Malmquist productivity index and meta-frontier analysis respectively. The later section presents the regression results of the relationship between TFEE and some economic factors and a summary of the chapter.

5.1 Descriptive Statistics of Variables

In performing any quantitative analysis, a common practice is to describe the data used. Given that the data used in this study is panel in nature, the choice is between pooling all the various years together or performing a year on year analysis. Pooling the data means one is of the assumption that years do not matter. Thus, assuming that the economic factors (such as inflation, economic growth, exchange rate dynamics and political instabilities (if any) underlining each year is the same, thus having no effect on the distribution of the variables. To this effect, a one-way dependent ANOVA was used to test for differences between years (see Appendix A for results). The test statistic was significant at the 5% level for all the variables; capital stock, real GDP, labour, energy, CH_4, N_2O and CO_2. For this reason a year on year descriptive analysis was performed for the variables. Table 5.1 however, presents descriptive statistics for the pooled data.

From Table 5.1, it is seen that the standard deviations of all the variables are above the various means. This is also supported by the year by year descriptive statistics for all the years under study. This seems to suggest a non-proportional relationship between the inputs and outputs, meaning that size does matter, thereby providing support for assuming a VRS production technology for the efficiency estimations. However, this can be considered a crude way of testing for the scale elasticity property. Hence, a test of returns to scale was later performed to confirm or reject this fact. Appendix B presents the descriptive statistics for the continental groupings.

Table 5.1: Summary Statistics for Inputs and Outputs-Pooled Data (2000-2014)

Descriptive statistics of key variables

	Variables	Mean	Std. Dev.	Min.	Max.	Count
Inputs	Capital	98594741646.11	353511113514.68	27568.89	4721377102256.08	1962
	Labour	22091756.81	79304723.38	106027.00	786573327.00	1962
	Energy	2424.62	2630.45	56.93	18178.14	1962
Outputs	GDP	12999.75	17945.07	138.44	119225.38	1962
	CO2	219285.91	826441.93	102.68	10291926.88	1962
	CH4	53503.20	154460.83	99.50	1752290.14	1962
	N2O	21088.46	58098.65	35.46	587166.37	1962

Count=Number of observations, std. Dev. =Standard deviation, min=Minimum value, max=Maximum value.

Before estimating efficiency under DEA, it is prudent to test whether the inputs and outputs satisfy the isotonic property. This was done by way of performing correlation analysis between the inputs and outputs with the results reported in Table 5.2. For variables to be considered as good inputs and outputs and to satisfy the isotonic property, all inputs should have a positive correlation with each of the outputs, meaning that increasing a particular input should not lead to a decrease in the outputs. From Table 5.2, with the exception of the relationship between labour and GDP, all inputs show highly positive and significant relationships with the outputs except energy.

Table 4.2: Correlation Analysis between Inputs and Outputs

	Capital	Labour	Energy	GDP	CO2	CH4	N2O
Capital	1.00						
Labour	0.58***	1.00					
Energy	0.35***	-0.13*	1.00				
GDP	0.49***	-0.15**	0.83***	1.00			
CO2	0.74***	0.72***	0.51***	0.44***	1.00		
CH4	0.53***	0.90***	0.05	-0.05	0.75***	1.00	
N2O	0.57***	0.90***	-0.04	-0.06	0.68***	0.92***	1.00

*,**,*** denote significance at 5%, 1% and 0.01% respectively

There is a highly significant positive relationship between energy and GDP (83%) showing that energy is significant in the study. There is also a high significant relationship between energy and CO2 estimating energy efficiency without considering CO2 emissions might not reflect the true state of efficiency. The other bad output all show a significant relationship with most of the other variables. Table 5.2S therefore suggests that the isotonicity assumption is satisfied.

5.2 Test for Returns to Scale

In efficiency analysis, a choice can be made to select either CRS or VR but this choice of selection has implications for the efficiency results. To this effect, the first objective of this study was to test for the appropriate scale elasticity property in the energy sector of the selected countries.

To achieve this objective, the study relied on the test procedures of Simar and Wilson (2002). The null hypothesis of the technology being CRS is tested against the alternate hypothesis of a VRS technology. The result presented in Table 5.3 provides support for the rejection of the null hypothesis at the 0.1% level, and conclude that the technology within which they operate is VRS. Thus the energy sector is characterized by a non-proportional relationship between inputs and outputs. The implication is therefore that increasing inputs may lead to an output increasing by more or less than the increase in the input. Knowing this helps in forecasting for a certain level of output. That is by how much inputs should be increased to attain a certain output level.

Table 5.3: RTS Test

Table 5.3*:* Test of RTS

TEST STAT	**0.6644**
CRIT VALUE	**0.9954**
P-VALUE	**0.0007**

5.3 TFEE of Countries

Estimations of the TFEE of the countries for the study period is presented in this section. All estimations are performed with the MaxDEA Ultra software.

5.3.1 TFEE of Countries

The second objective of the study sought to answer the question on the level of TFEE of countries in the study. To achieve this objective, the TFEE of each of the selected countries under the study was estimated using the undesirable-SBM under VRS where the undesirable or environmental factors are CO2, CH4 and N2O. These environmental factors have externalities on the environment which arise when an individual's welfare is affected by the actions of others, and its impact is not compensated. Without coordinated action by the government and industry to address these external costs, society as a whole will continue to bear the excess costs from these greenhouse gas emissions that are not reflected in market prices. There are environmental policy tools such as taxes and tradable permits that helps to internalize these external cost resulting in pollution control (Eyre, 1997; Pearce & Warford, 1993). Some of the countries are better able to reduce (internalize) the externalities associated with their productions and therefore improve upon their efficiency. The full results are attached in Appendix C.

Table 5.4 reports the average yearly TFEE of the countries for generalization purposes. The TFEE was estimated based on each year-specific frontier rather than a pooled frontier, due to the differences between variables for the various years.

It can be inferred from Table 5.4 that over the study period, most countries on average achieved a TFEE score of 39%, as suggested by the arithmetic mean. The implication therefore is that the selected countries employ more energy (electricity, coal, gasoline etc.) to produce less GDP whilst producing higher amounts of CO2, CH_4 and N2O.

Table 5.4: Yearly Average TFEE of Countries

YEARS	Biased Corrected Score	Bias	SD	LB	UB
2000	0.33	0.38	0.44	-0.82	0.39
2001	0.33	0.29	0.35	-0.58	0.39
2002	0.30	0.36	0.44	-0.88	0.35
2003	0.30	0.35	0.42	-0.80	0.35
204	0.18	1.00	1.03	-2.47	0.22
2005	0.19	0.85	0.93	-2.29	0.23
2006	0.21	1.76	2.35	-6.28	0.23
2007	0.38	0.36	0.55	-1.10	0.35
2008	0.49	0.51	0.89	-1.86	0.46
2009	0.48	0.52	1.01	-2.16	0.46
2010	0.49	0.42	0.67	-1.32	0.46
2011	0.47	0.57	0.99	-2.19	0.45
2012	0.54	0.30	0.38	-0.51	0.53
2013	0.55	0.38	0.63	-1.14	0.54
2014	0.53	0.27	0.30	-0.29	0.52
AVERAGE	**0.39**	**0.55**	**0.76**	**-1.65**	**0.40**

Score=Original Score, Score=Bias corrected score, SD=Standard Deviation, LB=Lower Bound, UB= Upper Bound*

The result in Table 5.4 shows that efficiency in the energy sector has generally been high in the earlier and the latter years. The years 2004 and 2005 recorded the lowest TFEE score of 0.18 and 0.19 respectively whereas year 2013 recorded the highest efficiency score of 0.55. The result also suggests that on average, the selected countries can reduce their energy consumption and emissions level whilst simultaneously increasing real GDP by 61%. This suggests a high level of energy savings potential for the selected countries.

Appendix C presents the average TFEE of the sampled countries for the entire study period from 2000 to 2014. To avoid making wrong inferences, both the geometric and arithmetic means are reported.

The table reveals that only two countries (Trinidad &Tobago and Barbados) appeared efficient with and without incorporating environmental factors. All other countries which were inefficient without the inclusion of environmental factors became efficient after their inclusion in the analysis. Cyprus, Iceland, Switzerland, Luxembourg, Zambia, Belize, Comoros, and Equatorial Guinea with efficiency scores of (0.948, 0.478, 0.957, 0.701, 0.343, 0.753, 0.782 and 0.181) respectively which were all inefficient without the incorporation of environmental factors had an efficiency score of 1 after the incorporation of the environment factors and were on the frontier. These countries are therefore the best performing TFEE countries, and can thus be said to have the best level of technology and production process, in transforming inputs into outputs. Hsieh, Lu, Li, Chiu, & Xu (2019) in their study on environmental assessment of European countries found out that Cyprus Luxembourg and Iceland were all efficient which is line with the current observation.

Out of the 135 countries considered in the study, 111 countries had an average TFEE below 50% after the inclusion of the environmental factors, with the worst performing countries being China, Russian Federation, Ukraine Iran, Islamic Republic, Uzbekistan, India, South Africa, Indonesia, Thailand, Kazakhstan, Saudi Arabia, Nigeria, Turkmenistan, United States, Korea, Republic, Vietnam, Pakistan, Malaysia, Belarus Poland, Egypt, Czech Republic, Venezuela, Canada, and Mexico with average TFEE levels of below 10%. These countries show more room for energy savings, which can be achieved by adjusting technology levels and production processes to the levels demonstrated by the frontier countries.

5.3.2 The Bootstrapped TFEE of Countries with and without Environmental Factors

Table 5.5: Average Yearly Bootstrapped TFEE of Countries

	Without environmental factors					With environmental factors				
YEARS	Biased corrected Score	Bias	SD	LB	UB	Biased corrected score	Bias	SD	LB	UB
2000	0.23	0.10	0.18	-0.03	0.58	0.33	0.38	0.44	-0.82	0.39
2001	0.21	0.09	0.15	-0.04	0.46	0.33	0.29	0.35	-0.58	0.39
2002	0.20	0.12	0.17	-0.10	0.53	0.30	0.36	0.44	-0.88	0.35
2003	0.20	0.12	0.17	-0.09	0.51	0.30	0.35	0.42	-080	0.35
2004	0.21	0.10	0.16	-0.04	0.51	0.18	1.00	1.03	-2.47	0.22
2005	0.22	0.11	0.18	-0.06	0.56	0.19	0.85	0.93	-2.29	0.23
2006	0.19	0.13	0.20	-0.11	0.46	0.21	1.76	2.35	-6.28	0.23
2007	0.22	0.10	0.15	-0.04	0.49	0.38	0.36	0.55	-1.10	0.35
2008	0.21	0.08	0.14	-0.02	0.47	0.49	0.51	0.89	-1.86	0.46
2009	0.20	0.13	0.17	-0.11	0.48	0.48	0.52	1.01	-2.16	0.46
2010	0.21	0.11	0.14	-0.08	0.41	0.49	0.42	0.67	-1.32	0.46
2011	0.21	0.10	0.15	-0.06	0.52	0.47	0.57	0.99	-2.19	0.45
2012	0.22	0.08	0.13	-0.01	0.45	0.54	0.30	0.38	-0.51	0.53
2013	0.21	0.11	0.14	-0.08	0.47	0.55	0.38	0.63	-1.14	0.54
2014	0.20	0.10	0.13	-0.05	0.43	0.53	0.27	0.30	-0.29	0.52
AVERAGE	**0.21**	**0.1**	**0.16**	**-0.06**	**0.49**	**0.39**	**0.55**	**0.76**	**-1.65**	**0.4**

Score=Original Score, Score=Bias corrected score, SD=Standard Deviation, LB=Lower Bound, UB= Upper Bound*

The third objective was achieved by estimating the bootstrapped TFEE of the countries with and without the inclusion of environmental factors using the bootstrap procedures of Simar and Wilson (1998) and then using two non-parametric tests (SZAL and Mann Whitney) and a parametric test (t-test) to check if there is a statistically significant difference in the scores.

Table 5.5 presents the results after performing 2000 bootstrap replications of the original data. The bootstrap purge off all biases that may arise due to sampling variations and measurement errors hence there is an expectation for lower TFEE scores after the bootstrap.

For the yearly averages, the bias corrected scores suggest that on average, countries are efficient in terms of energy efficiency as measured by the TFEE. Without the inclusion of environmental factors, the average yearly TFEE is 0.21 suggesting that the countries are on average 21% efficient. But with the inclusion of the environmental factors, an overall average bias corrected score of 0.39 suggests that the countries are 39% efficient revealing an increase in efficiency but the individual observations show that 2004 and 2005 had their scores reduced indicating that the countries could not internalize their externality cost. Zhongshan Yang (2019) found out in their study of The Belt and Road Initiative (BRI) countries that incorporating environmental factors led to an increase in efficiency scores. It can therefore be concluded not incorporating the environmental factors leads to biased scores.

In order to determine whether the differences established with and without the incorporation of environmental factors comparison above are significant, Simar-Zelenyuk-adapted-Li Test (Li, 1996; Simar & Zelenyuk, 2006), (SZAL) is employed. The SZAL test uses kernel density estimators to compare the distribution of the entire dataset unlike other tests of differences such as Independent t-test and Mann Whitney U tests which only compare point estimates and neglect the distribution of the entire dataset, SZAL test considers the distribution of the entire dataset (Li, 1996; Simar & Zelenyuk, 2006). To ensure robustness, the pairwise comparison of the means and ranks of the various groups is first done using traditional statistical techniques, Independent t-test and Mann Whitney U tests and subsequently, the SZAL is employed to test the differences in the entire dataset. The test statistics are presented in Table 5.6 together with p-values in parenthesis. Note that group efficiencies are not compared in this table since the group efficiency scores of the various groups are based on distinct production frontiers.

Table 5.6: Test for TFEE Differences between Groups

TEST	Null hypothesis (Ho)	Statistics	p-value
Mann- whitney u-test	(TFEE) WITH = (TFEE) WITHOUT	2741900	0.0000
SZAL		107.2162	0.0000
t-test		19.667	0.0000

From table 5.6 the results show that there is a statistically significant difference in the efficiency scores with and without incorporating the environmental factors. Thus, one can confidently conclude that accounting for environmental factors in the analysis results in the most total factor energy efficiency of the countries given that they have the highest average TFEE scores for the period.

5.3.3 Dynamic Productivity in the Energy Sector

The fourth objective of this study is to determine the dynamic productivities of the countries and to determine the source of the change using Malmquist dynamic productivity indices with and without incorporating environmental factors. The goal is to ascertain whether productivity is progressing, stagnating or retrogressing. The index is a biannual index that estimates productivity growth between two adjacent time periods. The yearly averages of the estimated productivity indices are shown in Table 5.7 as “MPI”. Geometric means are used since DEA efficiency estimates are ratios and can be skewed.

Table 5.7: Malmquist productivity index and Decomposition

With Environmental factors				Without environmental factors			
YEAR	**MPI**	**EC**	**TC**	**YEAR**	**MPI**	**EC**	**TC**
2000-2001	0.9627	1.0468	0.9257	**2000-2001**	0.9779	0.9972	0.9816
2001-2002	1.0265	0.9153	1.1477	**2001-2002**	1.0450	0.9521	1.1002
2002-2003	1.0548	1.0253	1.0375	**2002-2003**	1.1066	0.9793	1.1338
2003-2004	1.1228	0.5158	3.4072	**2003-2004**	1.1237	0.9102	1.2413
2004-2005	1.0932	1.0673	1.0242	**2004-2005**	1.1204	1.0610	1.0570
2005-2006	1.1648	1.0649	1.1330	**2005-2006**	0.1738	0.1738	0.1738
2006-2007	1.3916	1.4294	1.0158	**2006-2007**	1.4897	1.8166	0.8966
2007-2008	1.1126	2.4984	0.6382	**2007-2008**	1.1305	1.0747	1.0574
2008-2009	0.9648	0.9743	0.9900	**2008-2009**	0.9489	0.9739	0.9749
2009-2010	1.0659	1.0850	0.9851	**2009-2010**	1.0951	1.0852	1.0332
2010-2011	1.0696	1.0019	1.0636	**2010-2011**	1.1167	1.0061	1.1110
2011-2012	0.9768	1.2940	0.8142	**2011-2012**	1.0727	1.1254	0.9531
2012-2013	1.0102	0.9855	1.0439	**2012-2013**	1.0401	0.9553	1.0906
2013-2014	1.0049	0.9929	1.0138	**2013-2014**	1.0749	0.9894	1.0880
GEOMEAN	1.0681	1.0751	1.0684	**GEOMEAN**	0.9618	0.9267	0.9249

Where MPI= Malmquist productivity index, EC= Efficiency change, TC= Technical change

Preliminary results from Table 5.7 shows that with the incorporation of environmental factors the productivity of countries in the sample have progressed by an average of 6.81% (. i.e. [1.0681-1]*100) annually during the period covered by the study. This is primarily fuelled by periods of productivity growth in 2001-2002 (2.65% growth) and marginal growths in 2002-2003 (5.48%), 2003-2004 (12.28%), 2004-2005 (9.32%), 2005-2006 (16.48%), 2006-2007 (39.16%), 2007-2008 (11.26%), 2009-2010 (6.59%), 2010-2011 (6.96%), 2012-2013 (1.02%) and 2013-2014 (0.49%). Biannual estimates of productivity mostly showed progress for all periods except for 2001-2002, 2008-2009 and 2011-2012. The growth in 2006-2007 of 39.16% is the most significant growth during the period; this is followed by a 16.48% growth in 2005-2006 and 12.28% in 2003-2004.

This is important since it shows that, although the average productivity for the entire period progressed, productivity change in some of the individual years showed retrogression.

It can also be seen from the table that without the inclusion of environmental factors the productivity of countries in the sample have retrogressed by an average of 3.82% (0.00382) annually during the study period. Biennial estimates of productivity mostly showed progress for all periods except for 2001-2002, 2001-2002, 2005-2006 and 2008-2009.

Although knowledge of the extent of productivity change in the industry for the sample period has been understood, what remains unknown is the cause of the productivity situation. Suitable explanations to this can be gained by decomposing the Malmquist productivity indices.

Table 5.7 shows the two-factor decomposition of the Malmquist index by Fare et al (1992). Whereas EC (efficiency change) shows the part of productivity attributable to managerial decisions, TC (technical change) shows the part attributable to technological innovation. Careful inspection of TC and EC from Table 5.7 shows that the source of the overall productivity gain was mainly due to improvements in overall technological innovation and managerial acumen.

Decomposing the Malmquist productivity index shows that 7.51% growth per year is attributed to managerial decisions whilst on average 6.84% is attributed to technical growth with the inclusion of environmental factors. This shows that dynamic productivity is more associated with managerial decisions than technical change. In 2006-2007, for example, where 39.16% productivity gains were recorded, efficiency growth of 42.94% was recorded as against a 1.58% growth by technical gains. Similar deductions can be made for 2007-2008 period where there is a 149.84% growth in efficiency change with 36.18% decline in technical change and in the 2011-2012 period there is a 29.40% growth in efficiency change and 18.58% decline in technical change. It was only in 2003-

2004 that technical change recorded a higher growth of 240.72% with efficiency change having a decline of 48.42%. 2001-2002 also showed a 14.77% growth in technical change against 8.47% decline in efficiency change. Although an efficiency declines were recorded in both the EC and TC, TC outweighed that of the EC.

Without incorporating the environmental factors in the analysis shows that there is retrogression and decomposing it shows that 7.33% of the retrogression is due to efficiency change and 7.52% to technical change. The results show clearly that both the managerial innovation and technical change is the cause for the overall productivity growth and retrogression in both instances.

5.3.4 TFEE based on Continental Groupings

The fifth objective was to assess the efficiency of the countries based on continental groupings using the metafrotier analysis. The continental group comparison of the six continents is shown in Table 5.8 below. The average meta efficiency, group efficiency and TGR for each of the groups are presented and subsequently, ranks are assigned to these groups in descending order from the best performing to the worst performing group without and with the incorporation of the environmental factors to determine if the results vary. From Table 5.8, it is seen that without incorporating the environmental factor in the analysis AUS is the best performing continent in terms of TFEE whilst ASIA is the worst. With the incorporation of the bad output, it can be seen that AFR which ranked 5th when the bad output was not incorporated became the best performing continent in terms of TFEE whilst AUS countries which were the best performers are identified as the worst performers over the study period.

Table 5.8: **Energy efficiency with and without environmental factors**

With environmental factors					**Without environmental factors**				
Continent	Meta	Group	TGR	Rating	Continent	Meta	Group	TGR	Rating
AFR	0.31	0.38	0.83	1	**AFR**	0.10	0.18	0.53	5
EUR	0.30	0.36	0.81	2	**EUR**	0.21	0.21	0.99	2
ASIA	0.16	0.53	0.36	4	**ASIA**	0.10	0.19	0.48	6
SAM	0.21	0.66	0.33	5	**SAM**	0.15	0.37	0.41	4
AUS	0.15	1	0.15	6	**AUS**	0.23	0.87	0.26	1
NAM	0.28	0.64	0.49	3	**NAM**	0.17	0.34	0.46	3

TGR= Technological gap ratio, meta=metaefficiency, group=group efficiency

As detailed in Table 5.8 above, the group efficiency scores of both cases are quite high indicating that these continents within their local environments are performing well. It is evident that on the average, AUS countries are producing the optimum amount of output given their resources and the technology available with the bad output included in the analysis, whilst without the bad output in the analysis they produce 87%. AFR is producing 38% with the bad output in the analysis which reduces to 18% without the bad output given their group specific technologies. However, since the group efficiencies are computed relative to different production frontiers, it is inappropriate to compare the group specific efficiency scores of these different groups (Assaf et al., 2010; Oh & Lee, 2010). Therefore, the metafrontier results are used to compare the performance of these groups over time based on a common overarching frontier (Christopher O’Donnell et al., 2008). With the inclusion of bad output in the analysis, the average meta efficiency scores of AFR (0.31), EUR (0.30) and NAM (0.28) are the highest when measured against the country-wide frontier. Followed by these are the SAM, ASIA and AUS countries with meta scores of 0.21, 0.16 and 0.15 respectively which are all industrious economies and hence consume more energy resulting in higher emission levels. However, without the inclusion of the bad output, the efficiency is reduced, AUS (0.23) EUR (0.21) and NAM (0.17) are the highest when measured against the country-wide frontier. Followed by SAM, AFR and ASIA with meta score of 0.15, 0.10, 0.09 respectively. This indicates that when measured against the metafrontier without the environmental factors suppressed the efficiency scores.

A careful observation of the results shows that with the inclusion of the bad output AFR (0.83) and EUR (0.81) countries have TGRs very close to 1 indicating that AFR countries are producing at 83% of their potential output whereas EUR countries are producing at 81% of their potential output given the technology available to the continents while AUS countries attained the least average TGR of 0.15 demonstrating that AUS countries are producing about 15% of their potential output given the know-how, resources, infrastructure and institutions available to the continent as a whole. On other hand without the inclusion of the bad output shows that only EUR (0.99) countries have their TGR very close to one indicating that indicating that EUR countries are producing at 99% of their potential output whereas AUS (0.26) countries are producing at 26% of their potential output given the technology available to the continents. From the results above it can be seen that including the environmental factors changes the ratings of the various continents.

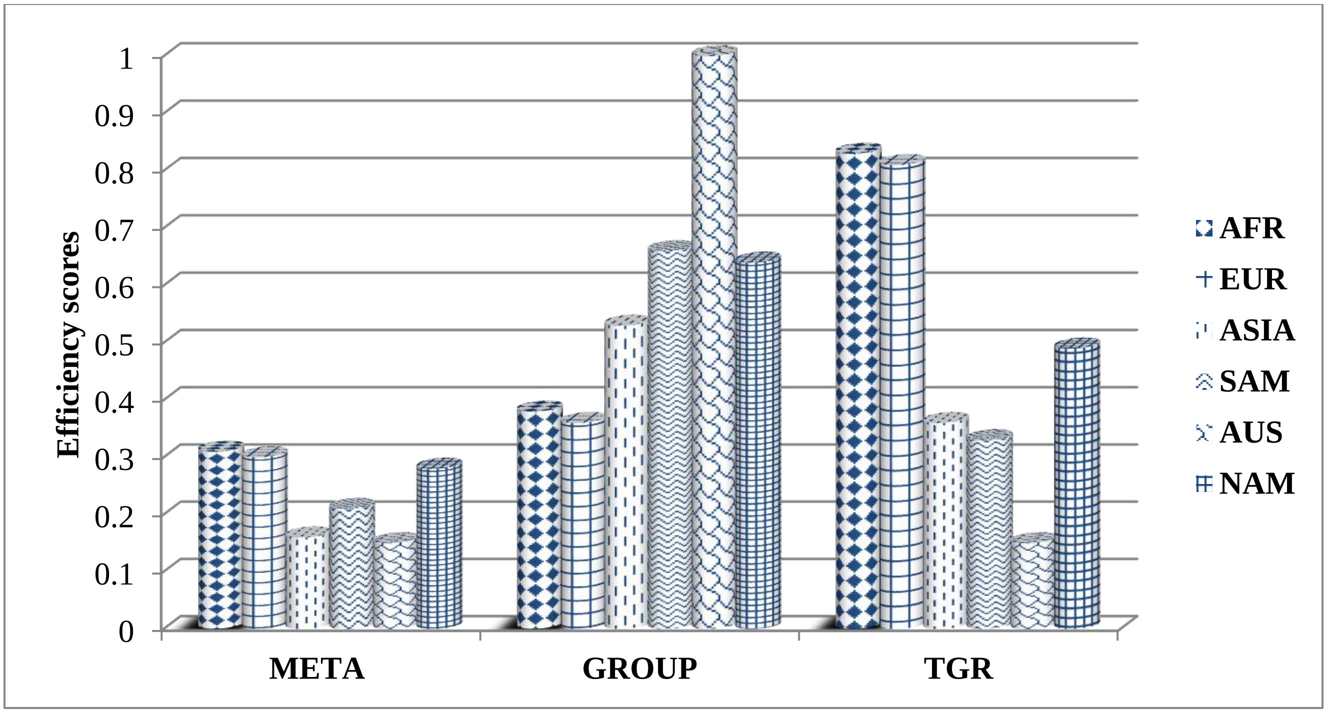


Figure 5.1: Distribution of TFEE by continental groupings with environmental factors

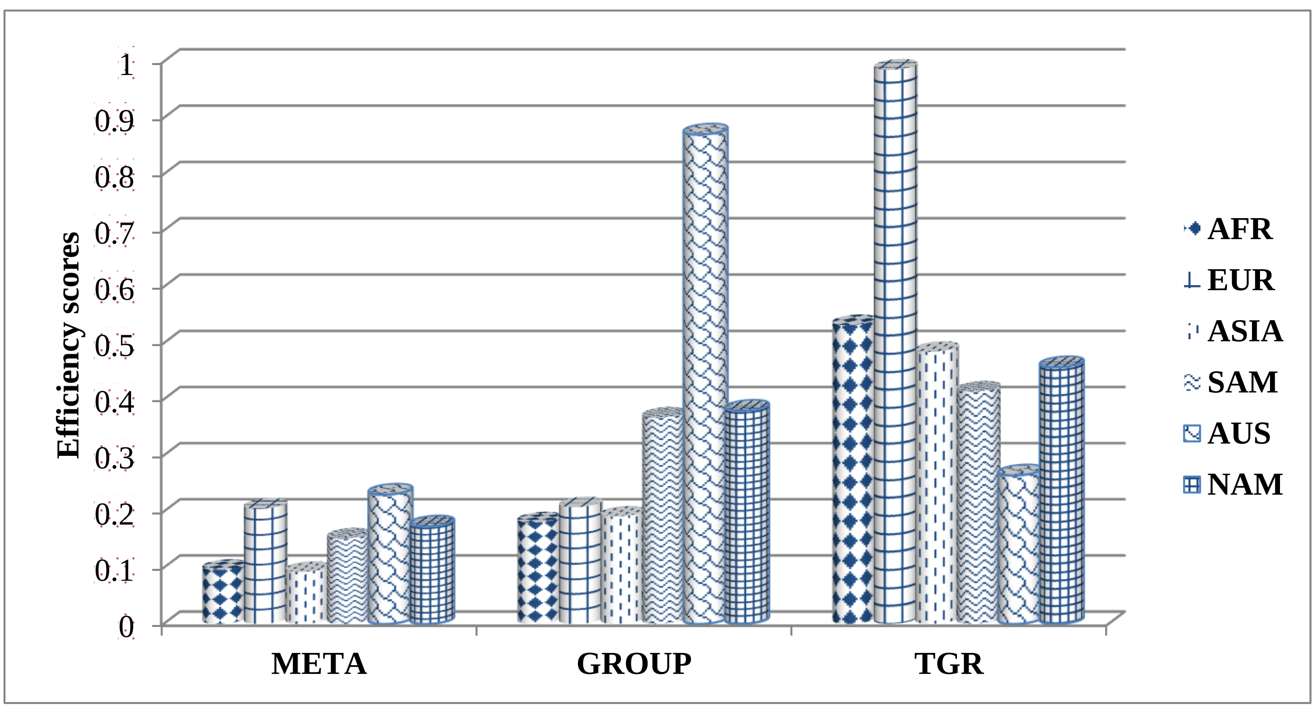


Figure 5.2: Distribution of TFEE by continental groupings without environmental factors

Figure 5.1 and 5.2 presents a graphical illustration of the distribution of the average meta efficiency, group efficiency and TGR of the different continents with and without the incorporation of environmental factors. The graphical representations allow for easy understanding of how the scores of a particular group differ from others. A glance at Figure 5.1 shows that on the average, AFR countries have the highest meta efficiency score, signifying the highest level of efficiency followed by EUR and NAM countries respectively with AUS being the last whiles figure 3 shows that on the average, AUS countries rather have the highest meta efficiency score, signifying the highest level of efficiency followed by EUR and SAM countries respectively with ASIA being the last. The group efficiency indicates that each of the groups is performing substantially well within their terrains, from both figures AUS countries are operating on at higher levels. The TGRs show evidently that with the incorporation of environmental factors AFR countries are the top in performance in the groupings, closely followed by EUR, AUS is the least performer whiles without the incorporation of environmental factors EUR countries are the top in performance in the groupings, followed by AFR, ASIA, NAM, SAM with AUS countries still being last.

Kernel Density plot of the distribution of the meta efficiency scores of the various continents with and without the incorporation of environmental factors are presented in Figures 4 and 5 below respectively for better visualization of the distribution of the meta scores.

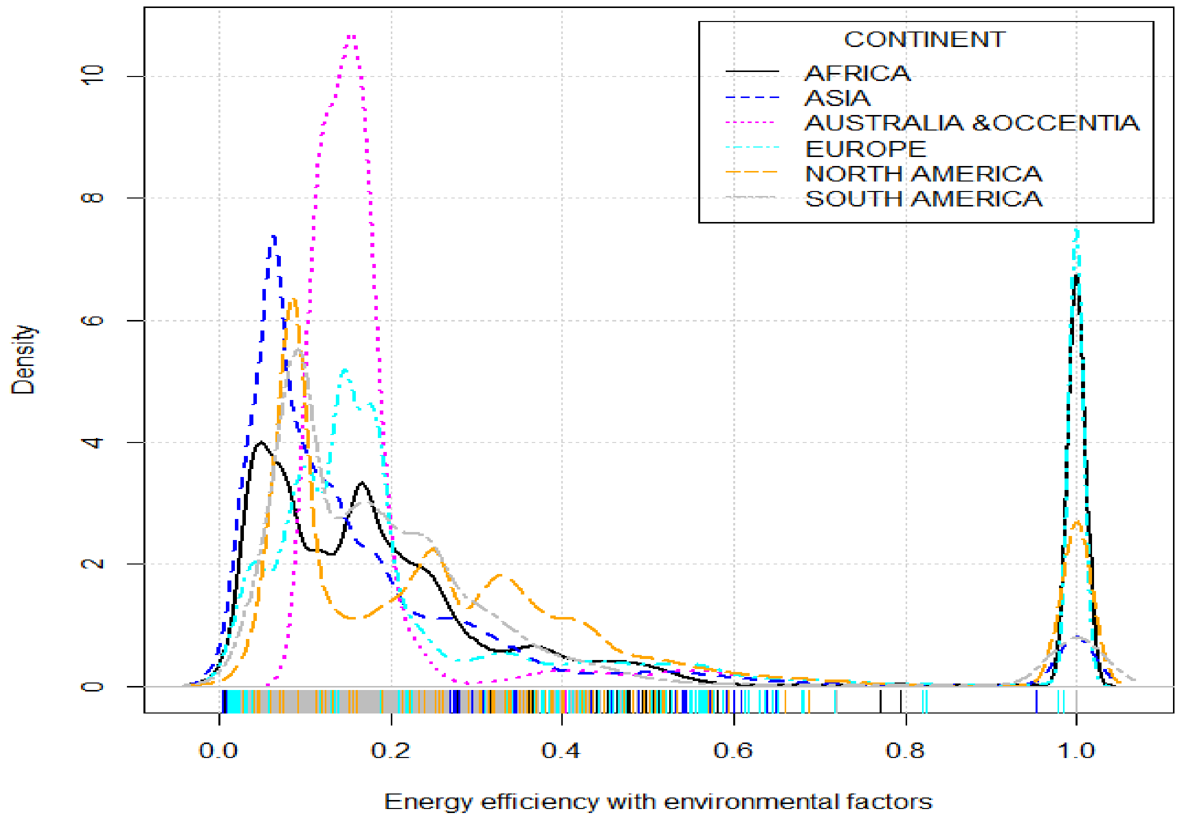


Figure 5.3: Kernel Density Plot of Meta scores with environmental factors

An observation of Figure 5.3 shows that African and European countries gather greater probability mass on the right tail suggesting that a greater number of the countries in these continents are located close to the efficiency boundary whilst Australian, Asian, North American and south American countries gather greater probability mass on the left tail signaling that greater number of the countries are located further away from the efficiency frontier.

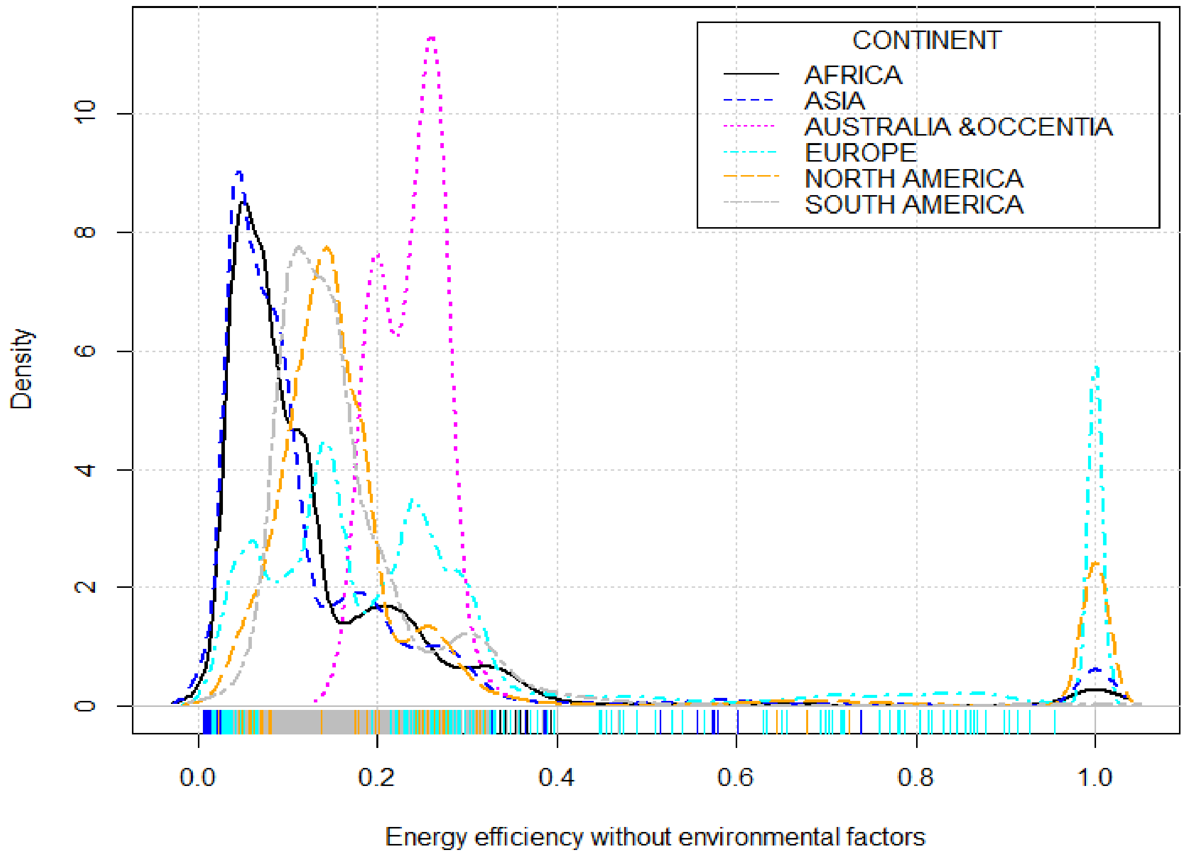


Figure 2.4: Kernel Density Plot of Meta scores without environmental factors

From Figure 5 above it can be seen that European countries gather greater probability mass on the right tail suggesting that a greater number of the countries in this continent are located close to the efficiency boundary whilst Australian, Asian, African, North American and south American countries gather greater probability mass on the left tail showing that greater number of the countries are located further away from the efficiency frontier.

5.4 Energy Efficiency and Economic Factors

Objective six was to test the relationship between TFEE and some economic factors. To achieve this, the study first employed OLS-PCSE regression approach to estimate the impact of some economic factors on TFEE whilst controlling for other variables. Results of TFEE relationship is presented using panel data models presented in Table 5.11 below. The robust analyses are presented in Table 5.11 below using different environmental factor proxies. Regression estimation using general least squares (GLS) in model 2 is justified by Breusch and Pagan Lagrangian multiplier test which shows that GLS (RE or FE) estimation is more appropriate and robust than the OLS. Also, the choice of FE or RE in this study is based on the Hausman test. A p-value > 0.05 for the Hausman test indicates that RE is preferred under GLS estimation and a p-value < 0.05 indicates that FE model is preferred under GLS estimation. Due to the potential endogeneity resulting from the reverse causality between efficiency and some environmental factors which could result in bias estimations (Roberts & Whited, 2013; Williams, 2012), the regression analysis is estimated using the OLS-PCSE, 2SLS and two step system GMM approach as indicated in models 1 3 and 4 respectively. In this study, two-step system GMM is most preferred because it is more robust to autocorrelation, heteroscedasticity and also in controlling for potential endogeneity. Two-step system GMM compared to the truncated bootstrap uses optimal weighting matrix and also relaxes the assumption of independently and identically distributed (Arellano & Bover, 1995; Blundell & Bond, 1998; Cummins, Rubio-Misas, & Vencappa, 2017). Hence, analysis and conclusions are based on the preferred model (system GMM). In conclusion, the regression model is first estimated with OLS and for robustness checks, GLS, 2SLS and system GMM are used for the estimations. All conclusions are based on the system GMM.

Table 5.9 resents the summary statistics of the variables used in the second stage OLS-PCSE regression 2SLS, GLS and System GMM analysis.

Table 5.9: Descriptive statistics of the environmental variables

Variable	Count	Mean	Std.Dev.	Min	Max
SCORE	1951	0.382	0.31	0.005	1
CAPLAB	1951	5898.211	7713.156	0.015	51356.09
GNIPC	1933	9.185	1.142	6.043	11.524
INF	1820	6.672	18.831	-10.067	513.907
POPG	1694	1.345	1.458	-2.851	14.237
EXCH	1951	8.118	5.336	0.319	33.473
INT	1314	7.965	40.318	-60.781	1158.026
UNEMP	1592	3.464	2.483	0.044	10.127
DEBT	966	68.944	167.828	0	2013
AFR	1951	0.215	0.411	0	1
ASIA	1951	0.244	0.43	0	1
EUR	1951	0.322	0.468	0	1
NAM	1951	0.109	0.311	0	1
SAM	1951	0.094	0.292	0	1

Count=Number of observations, std. Dev. =Standard deviation, Min=Minimum value, Max=Maximum value.

For any regression analysis, first the degree of multicollinearity between the independent variables must be tested. According to Kennedy (2008), there is multicollinearity if the correlation coefficients are greater than 0.70. This is done by way of a correlation matrix as presented in Table 5.10. From the correlation matrix in Table 5.10 below, there is no evidence of multicollinearity since all the correlation coefficients are less than 0.70.

Table 5.10: Correlation matrix for the second stage variables

	TFEE	CAPL	GNIPC	INF	POPG	EXCH	INT	UNEM	DEBT	AFR	ASIA	EUR	NAM	SAM
TFEE	1.00													
CAPL	0.29	1.00												
GNIPC	-0.01	0.01	1.00											
INF	0.04	-0.02	-0.15	1.00										
POPG	0.01	-0.02	0.09	0.06	1.00									
EXCH	-0.01	-0.02	0.01	-0.03	0.03	1.00								
INT	0.02	-0.02	-0.01	0.00	0.06	-0.03	1.00							
UNEM	-0.01	0.00	0.03	0.00	0.06	-0.09	-0.05	1.00						
DEBT	-0.11	-0.06	-0.05	0.01	0.02	-0.03	-0.01	0.02	1.00					
AFR	0.04	-0.30	0.01	-0.02	0.01	-0.01	0.02	0.03	-0.01	1.00				
ASIA	-0.16	-0.08	0.00	-0.03	0.03	-0.02	-0.03	0.05	0.05	-0.30	1.00			
EUR	0.10	0.42	-0.02	0.01	-0.02	0.02	0.02	-0.08	-0.06	-0.36	-0.39	1.00		
NAM	0.06	-0.08	-0.01	0.04	0.01	-0.01	-0.02	-0.01	-0.03	-0.18	-0.20	-0.24	1.00	
SAM	-0.05	-0.13	0.02	0.03	-0.02	0.02	0.01	0.02	0.05	-0.17	-0.18	-0.22	-0.11	1.00

From the correlation matrix, it is seen that income per capital (GNIPC) and TFEE are negatively related.

Table 5.11: TFEE-environmental factors Regression Results

VARIABLES	(1) OLS-PCSE	**(2) FE**	**(3) 2SLS Model**	**(4) SYS GMM**
L.score				0.758***
				(-0.123)
CAPLAB	4.28e-05***	0.0722***	1.34e-05***	4.62e-06**
	(9.49e-06)	(-0.0256)	(-2.16E-06)	(-1.84E-06)
GNIPC	-3.13e-06	-0.0193	-4.80E-07	0.0047
	(3.05e-06)	(-0.0118)	(-8.25E-07)	(-0.00697)
INF	-0.00151	-0.0105	-0.000458***	0.000127
	(0.00106)	(-0.0133)	(-0.000151)	(-0.000238)
POPG	0.00116	-0.0118	0.00306	-0.00131
	(0.0364)	(-0.00433)	(-0.00853)	(-0.00423)
EXCH	-0.00680	-0.000392	-0.00498*	-0.00243*
	(0.00618)	(-0.00188)	(-0.00274)	(-0.0014)

INT	0.00470***	0.00239	0.00118	0.000184
	(0.00166)	(-0.0122)	(-0.00106)	(-0.00038)
UNEMP	-9.02e-06	0.00358	-6.53E-06	-0.0103
	(2.43e-05)	(-0.00483)	(-6.20E-06)	(-0.0092)
DEBT	-0.000233	-0.0248**	-7.18e-05*	-6.04e-05***
	(0.000240)	(-0.0118)	(-3.93E-05)	(-2.30E-05)
AFR	0.464*	0.231	0.101**	0.112*
	(0.241)	(-0.154)	(-0.0495)	(-0.0636)
ASIA	-0.00627	0.0976	-0.0389	0.0822
	(0.242)	(-0.189)	(-0.0433)	(-0.0526)
EUR	0.184	0.0789	-0.11	0.0921
	(0.185)	(-0.189)	(-0.0895)	(-0.0577)
NAM	0.606**	0.212	0.000594	0.156**
	(0.259)	(-0.183)	(-0.0455)	(-0.0638)
SAM	0.247	0.0629	0.132**	0.104*
	(0.222)	(-0.172)	(-0.0598)	(-0.0554)
Constant	-1.755***		0.318***	
	(0.239)		(-0.0425)	
$\boldsymbol{Wald\ \chi^2}$	345.28			
$\boldsymbol{Prob > \chi^2}$	0.0000			
$\boldsymbol{R^2}$	0.1294		0.138	
$\boldsymbol{Hettest: Prob > \chi^2}$	0.0000			
$\boldsymbol{AR(1): Prob > F}$				0.061
$\boldsymbol{BPL: Prob > \chi^2}$		0.040		
F test				
$\boldsymbol{Prob > F}$		0.000		0.000
Hausman		21.88		
$\boldsymbol{Prob > \chi^2}$		0.0027		
$\boldsymbol{Hansen\ J\ \chi^2 Prob > \chi^2}$ **)**				0.688
$\boldsymbol{AR\ (2): Prob > F}$				0.174
Instruments				34
Observations	452	383	371	413

Note: Hettest = heteroscedasticity; AR(1) = first order autocorrelation; AR(2) = second order autocorrelation; R^2 *= R-squared;* ***BPL= Breusch and Pagan Lagrangian multiplier test***

Robust Standard errors in parentheses

*** p < 0.01, ** p < 0.05, * p < 0.1

The statistically insignificant Hansen J statistics under the 2SLS shows that the instruments used in the regression are valid, thus they are not correlated with the disturbance term. Finally, for the validity of the system GMM, the three requirements are met as shown in model 4. First, there is no second order autocorrelation as indicated by the p-value (0.174). Second, the Hansen J statistics is statistically insignificant indicating that the instrumental variables are not related with the disturbance term, thus they are valid. Finally, the number of instruments is less than the number of observations used in the study.

The regression result in Table 5.11 under the system GMM which is the preferred model (model 4) shows that contrary to the study by Kumar (2006) technological progress, proxied by the capital-labor ratio, is reported to have a significantly positive influence on TFEE. Studies by Apergis et al. (2015), Zhao Xiaoli et al. (2014) and Fang et al. (2013) all found similar results.

Wu (2012) hypothesized that the capital–labour ratio reduce inefficient energy use, because new capital utilizes energy-saving technology. Thus, countries that are more capital intensive are more energy efficient than labor intensive countries.

The table also shows that income per capita (GNIPC) has a positive effect on TFEE as reported by Jebali (2017) in their study energy efficiency of the Mediterranean countries. A study by Chang and Hu (2010); Xiaoli, Rui, & Qian (2014) also found a positive relation between income per capita and total factor energy productivity index in China. This suggests that highly developed countries are more energy efficient than their least developed counterparts. These highly developed countries have the necessary structures put in place to ensure high energy savings. These include policies on energy efficiency, use of renewable energy, and investment in energy savings technologies.

Lag of the efficiency score shows a positively significant relationship suggesting that the efficiency of a country at a particular time period positively affects the efficiency of the next period significantly. This suggests the need of development through sustainable energy use. One way of achieving this could be through the use of clean and renewable energy such as solar, which have little negative environmental impacts.

Debt stock has a negative significant relationship with TFEE of countries which suggest that countries with high debtusually have low efficiencies. Countries are able to shift their environmental effect of emission to the other countries that owe them, either by physically relocating the firm or outsourcing parts of its production lines.

Population growth is found to have a negative relationship with TFEE of countries. This means that as population grows, less useful economic output is produced with more energy.

Interest rate and inflation both have a negative insignificant relationship with TFEE levels of countries.Exchange rate has a negative significant relationship with TFEE levels of the countries. Most of the continental dummies showed a positive significant relationship with TFEE of the countries which suggest that the continent a country finds itself has an effect on the effeciency levels.

5.5 Chapter Summary

This chapter presented the results achieved from running the various models to answer the research objectives. It started with a presentation of the descriptive statistics of the input and output data used in estimating the TFEE of the selected countries. The first objective of the study was achieved by testing the scale elasticity property of the energy sector. The results showed that the energy sector of the selected countries exhibits the VRS property.

The second objective was achieved by estimating the bootstrap TFEE levels of the countries, which showed that the countries were on average 39% energy efficient over the study period. The result suggests that on average, the selected countries can reduce their energy consumption and CO2 emissions levels whilst simultaneously increasing real GDP by 61%. The results also showed that out of the 135 countries understudy, 6 were efficient throughout the period, 4 efficient in the years they appeared in the study, 98 were inefficient throughout the period whiles 27 were efficient for some years and inefficient for others

The third objective was achieved by estimating the bootstrapped TFEE of the countries with and without the inclusion of environmental factors and then using the Mann whitney, SZAL and t- test to check if there is a significant difference in the scores. The results showed that without the inclusion of environmental factors the average yearly TFEE is 0.21 whilst with the inclusion of the environmental factors it is 0.39 revealing an increase in efficiency. The Mann whitney, SZAL, and t-test all had p-values (0.000) showing that the differences in the efficiency scores with and without including the environmental factors is statistically significant.

The fourth objective was achieved using the Malmquist dynamic productivity indices to determine the dynamic productivities of the countries and to determine the source of the change. The results showed that incorporating environmental factors in the analysis, the productivity of countries in the sample have progressed by an average of 6.81% annually during the sample period and decomposing the malmquist productivity index shows that 7.51% growth per year is attributed to managerial decisions and 6.84% is attributed to technical growth whilst without the environmental factors in the analysis, the productivity of the countries retrogressed by an average of 3.82% annually.

The fifth objective was achieved by applying the metafrontier analysis, the results showed that AFR countries are the best performers in energy efficiency followed by EUR, NAM, ASIA, SAM and lastly by AUS countries respectively with bad outputs in the analysis whilst without adding the bad output to the analysis showed that AUS, EUR and NAM are the best performers when measured against the country-wide frontier followed by SAM, AFR and ASIA respectively. This indicates that when measured against the metafrontier without the environmental factors affects the efficiency scores.

For the second stage analysis, the TFEE was regressed on environmental factors, using the OLS-PCSE, FE, systems GMM and the 2SLS method. The results revealed that income per capita (GNIPC) has a positive effect on TFEE, depicting that countries that are more capital intensive are more energy efficient than labor intensive countries. Technological progress (CAPLAB), proxied by the capital-labor ratio, is reported to also have a significantly positive influence on TFEE. Debt stock has a negative significant relationship with TFEE.

CHAPTER SIX

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

6.0 Introduction

This chapter is devoted to the summary, conclusions and recommendations from the study and consists of three sections. The objectives of the study as well as the key findings are presented in the first section, the second section draws conclusions from the findings whereas recommendations for policy, practice and directions for further research are provided in the final section.

6.1 Summary of the study

The purpose of this study was to investigate the impact of incorporating environmental factors on the energy efficiency of the selected countries. Although there are a number of studies on energy efficiency, this study was unique in many ways: the study investigated the TFEE of selected countries across the globe. Also, unlike other studies, the study accounted for the economic factors or dual factors that affect energy efficiency but are out of the control of management such as population growth, inflation and income. Additionally, the study incorporated group heterogeneity in its assessment by assessing the TFEE based on continental groupings.

Data of 135 selected countries due to data scarcity for the period 2000-2014 was sourced from World Bank indicators (WDI). Data on labor, capital, Energy and CO2, N2O, CH_4, real GDP and other macroeconomic variables were also sourced from World Development Indicator. In all 135 countries for 15 years gave 1962 individual observations for the study.

The data was first analyzed by presenting the summary statistics and returns to scale test and subsequently the research objectives. The countries were grouped into continents to statistically compare TFEE of countries based on continental groupings and to investigate the impact of some economic factors on the TFEE of the selected countries.

The study applied non-parametric estimations, particularly the SBM of Tone to estimate TFEE of the countries, in the presence of undesirable output. Bootstrapping procedures of Simar and Wilson were applied to correct for biases in TFEE scores, the Malmquist productivity index was used to assess the productivity of the countries from year to year, whilst the metafrontier analysis technique was used to assess the TFEE distributions of the various continental groupings in the world. On the impact of economic factors on the TFEE of the countries, the study applied the OLS-PCSE, FE, 2SLS and systems GMM to assess the impact of economic factors on TFEE.

R-based statistical packages, MaxDEA Ultra 7, Excel, and STATA 13 were the primary software's used for estimations. The major findings identified in the study include:

a. The energy sector of the selected countries operates under the VRS production technology.
b. Of the 135 countries understudy, 6 were efficient throughout the period, 4 efficient in the years they appeared in the study, 98 were inefficient throughout the period whilst 27 were efficient for some years and inefficient for others.

c. The countries are on average only 39% total factor energy efficient over the study period. This implies that countries are 61% energy inefficient. Hence, the countries can simultaneously increase outputs and reduce inputs, CO2, CH4 and N2O levels by 61%, showing more room for energy savings. The most energy efficient countries are Cyprus, Iceland, Luxembourg, Switzerland, Trinidad and Tobago, Zambia Barbados, Belize, Comoros and Equatorial Guinea with the worst performing countries being China, Russian Federation, Ukraine Iran, Islamic Republic, Uzbekistan, India, South Africa, Indonesia, Thailand, Kazakhstan, Saudi Arabia, Nigeria, Turkmenistan, United States, Korea, Republic, Vietnam, Pakistan, Malaysia, Belarus Poland, Egypt, Czech Republic, Venezuela, Canada, and Mexico with average TFEE levels of below 10%

d. The productivity of countries in the sample progressed by an average of 6.81% annually with the inclusion of environmental factors whilst dropping these factors led to retrogression in the productivity index.

e. AFR countries are the most total factor energy efficient with average meta efficiency levels of 38% and TGR of 83%, followed by EUR countries with a meta efficiency of 36% and TGR of 81% and AUS countries being the least efficient with average meta efficiency levels of 15% and TGR of 15% over the study period, meaning AFR countries have the most energy efficient production process when environmental factors were included in the analysis, however without adding them in the analysis showed that AUS countries are the most efficient with meta efficiency 23% and TGR 21% followed by EUR with meta efficiency of 26% and TGR 0.99% and AFR, ASIA being the least efficient.

f. Technological progress (CAPLAB) is reported to have a significantly positive influence on TFEE which is contrary to the study by Kumar (2006). This implies that countries in the pursuit of energy efficiency should pay attention to technology to help solve issues such as global warming and energy security. It also showed that income per capita (GNIPC) has a positive effect on TFEE as reported by Jebali (2017) in their study energy efficiency of the Mediterranean countries.

6.2 Conclusions of the Study

The findings of the study have revealed some thought-provoking issues for consideration in efficiency assessments in the energy at the country level. First is on the scale of operation and its implications on productive capabilities of the countries. The test of returns to scale conducted showed the energy sector operates on variable returns to scale (VRS) implying that size matters. This therefore shows that there exist high opportunities for growth of the countries. This is an indication that not all countries examined are operating at optimal production scales. This means the ratio of inputs to outputs is not proportional, such that any doubling of the amount of energy consumed may lead to outputs increasing or decreasing by more than double. Impliedly, some of the countries could improve their efficiency by either increasing or reducing their scale of operation. Hence it now becomes necessary for policy makers to know whether they operate under increasing or decreasing returns to scale to know by how much to increase or decrease a particular input to achieve a certain level of growth. Countries should therefore evaluate their operations and either increase or reduce their scale of operation in order to enjoy economies of scale.

The second finding suggests that the countries have more to do in terms of translating energy consumption to economic growth, given the 61% average inefficiency levels. The implication of this result therefore is that countries employ more energy resources to produce relatively less GDP at higher emission levels.

Another finding suggests that incorporating environmental factors led to a progression in productivity by 6.81% annually and decomposing this productivity index showed that 7.51% growth per year is attributed to managerial decisions and 6.84% to technical growth whilst not incorporating led to retrogression in the productivity index.

On the issue of continental groupings and TFEE performance, the results suggest that the efficiency scores without environmental factors in the analysis turned out to be lower compared to when environmental factors were incorporated.

The findings of the OLS-PCSE, FE, 2SLS, systems GMM contradicted that of Kumar (2006) on the relationship between TFEE and technological progress (CAPLAB). This implies that countries in the pursuit of energy efficiency should pay attention to technology to help solve issues such as global warming and energy security. It also shows that income per capita (GNIPC) has a positive effect on TFEE as reported by Jebali (2017) in their study energy efficiency of the Mediterranean countries. This suggests that highly developed countries are more energy efficient than their least developed counterparts. Government should put in place the necessary structures to ensure high energy savings. These include policies on energy efficiency, use of renewable energy, and investment in energy savings technologies. Also supported is the need for government deregulations on borrowing from other countries.

6.3 Recommendations

Based on the findings and conclusions of the study, essential recommendations have been made for policy, practice and for future research. These are detailed below:

For policy:

a. First, there is a steady decrease in the energy efficiency over the period of 2002-2011 as shown by the results of the study. Albeit a few countries attained the best energy efficiency scores (Cyprus, Iceland, Switzerland, Luxembourg, Belize, Comoros, Trinidad and Tobago and Zambia), All other countries should adopt regulatory policies which focus on enhancing energy efficiency by Government expanding their interest in research and development and investing in it. Also through disseminating the right information and transfer of knowledge on measures to improve energy efficiency there is a significant opportunity for improvement in energy efficiency hence companies that have higher energy consumption must be reexamined.

b. Policy makers need to focus on Energy using products. This involves ensuring that all energy using appliances are correctly labeled according to their energy consumption levels. Strict monitoring is also required to ensure that only correctly labeled products find their ways onto the markets (Koskimäki, 2012). Also, the attention of individuals should be drawn to energy conservation and urged to adopt consumption behaviors that saves energy.

For practice:

a. Some of the countries are not operating on an optimal scale, it is up to management to evaluate their operations and either scale up or down their capacity in order to be efficient. This requires the investment into new modern technologies and opening up of economies to foreign investors. As such, the governments of countries need to strengthen the incentives for the technological progress of industries through regulatory policies by using both market and administration mechanisms.

b. Sustainable development can be achieved through energy-saving and cleaner production. This can be done through ensuring that the governments cooperate with the industries and that there is an effective communication framework through which energy-saving and emission-reducing experiences can be passed. Regulations on cleaner production ought to be advanced and carefully implemented. This would prompt the companies accepting cleaner production as a major errand and giving it more attention.

c. Foreign and research investments ought to be viably utilized by the various companies together with governments. This should be regulated by governments to ensure that research projects can be enforced and if a company achieves high energy efficiency, its balanced productive proportion should be maintained to ensure high effective production progress.

For Further Research:

a. To substantiate the findings in this study, further studies could increase sample size and period to make all countries or groups more representative as well as include up-to-date data Subject to data availability to align findings with current technological, economic and political developments in the sector to assess the TFEE of all countries across the globe.
b. Future studies could consider decomposing the energy input into its various sources such as electricity, coal, gasoline, etc. other than using a composite measure of primary energy consumed. This will help reveal the energy resources that are most efficiently used and the ones least used. This study used a composite measure of primary energy consumed (i.e. combining all the various energy sources as one input) which does not help reveal the energy resources that are most and least efficiently used.
c. A recommendation is also made for studies to consider disaggregating the TFEE to assess the contribution of each input and output variable to the TFEE score. This will give policy makers a direct target, for example whether to focus on reducing CO2 emission, increasing real GDP, or reducing energy consumption to improve upon TFEE.

REFERRENCES

Adom, P. K. (2019). An evaluation of energy efficiency performances in Africa under heterogeneous technologies *Cleaner productions, 209*, 170e1181.

Aerts, W., & Cormier, D. . (2009). Media legitimacy and corporate environmental communication. *Accounting, organizations and society, 34*(1), 1-27.

Al-Tuwaijri, S. A., Christensen, T. E., & Hughes, K. E. . (2004). The relations among environmental disclosure, environmental performance, and economic performance: a simultaneous equations approach. *Accounting, Organizations and Society, 29*, 447-471.

Alberini, A., Filippini, M. (2018). Transient and persistent energy efficiency in the US residential sector: evidence from household-level data. *Energy Efficienc, 11*(3), 589-601.

Alhassan, A. L., & Ohene-Asare, K. (2016). Competition and bank efficiency in emerging markets: empirical evidence from Ghana. *African Journal of Economic and Management Studies, 7*(2), 268-288.

Ang, B. W. (2006). Monitoring changes in economy-wide energy efficiency: From energy–GDP ratio to composite efficiency index. *Energy Policy, 34*(5), 574-582. doi: http://dx.doi.org/10.1016/j.enpol.2005.11.011

Antweiler, W., Copeland, B. R., & Taylor, M. S. . (2001). Is free trade good for the environment? *American Economic Review, 91*(4), 877-908.

Apergis, N., Aye, G. C., Barros, C. P., Gupta, R., & Wanke, P. (2015). Energy efficiency of selected OECD countries: A slacks based model with undesirable outputs. *Energy Economics, 51*, 45-53. doi: http://dx.doi.org/10.1016/j.eneco.2015.05.022

Arabmazar, A., & Schmidt, P. (1982). An investigation of the robustness of the Tobit estimator to non-normality. *Econometrica: Journal of the Econometric Society*, 1055-1063.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of econometrics, 68*(1), 29-51.

Assaf, A., Barros, C. P., & Josiassen, A. (2010). Hotel efficiency: A bootstrapped metafrontier approach. *International Journal of Hospitality Management, 29*(3), 468-475.

Avkiran, N. K. (1999). The evidence on efficiency gains: The role of mergers and the benefits to the public. *Journal of Banking and Finance, 23*, 991-1013.

Bai-Chen, X., Ying, F., & Qian-Qian, Q. (2012). Does generation form influence environmental efficiency performance? An analysis of China's power system. *Applied Energy, 96*(0), 261-271. doi: http://dx.doi.org/10.1016/j.apenergy.2011.11.011

Banker, R., Natarajan, R., & Zhang, D. (2019). Two-stage estimation of the impact of contextual variables in stochastic frontier production function models using data envelopment analysis: second stage OLS versus bootstrap approaches. *European Journal of Operational Research, 278*(2), 368-384.

Banker R. D., M. R. C. (1986). Efficiency analysis for exogenously fixed inputs and outputs. *Operations Research, , 34*(1986), 513-521.

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Management Science, 30*(9), 1078-1092.

Banker, R. D., & Natarajan, R. (2008). Evaluating contextual variables affecting productivity using data envelopment analysis. *Operations research, 56*(1), 48-58.

Barros, C., & Assaf, A. (2009). Bootstrapped efficiency measures of oil blocks in Angola. *Energy Policy, 37*(10), 4098-4103.

Barros, C. P., Nektarios, M., & Assaf, A. (2010). Efficiency in the Greek insurance industry. *European Journal of Operational Research, 205*(2), 431-436. doi: http://dx.doi.org/10.1016/j.ejor.2010.01.011

Battese, G. E., & Rao, D. P. (2002). Technology gap, efficiency, and a stochastic metafrontier function. *International Journal of Business and Economics, 1*(2), 87-93.

Battese, G. E., & Rao, D. S. P. (2002). Technology gap, efficiency, and a stochastic metafrontier function. *International Journal of Business and Economics, 1*(2), 87-93.

Battese, G. E., Rao, D. S. P., & O'Donnell, C. J. (2004). A Metafrontier Production Function for Estimation of Technical Efficiencies and Technology Gaps for Firms Operating Under Different Technologies. *Journal of Productivity Analysis, 21*(1), 91-103. doi: 10.1023/b:prod.0000012454.06094.29

Beck, N., & Katz, J. N. (1995). What to do (and not to do) with time-series cross-section data. *American Political Science Review, 89*(3), 634-647.

Bewley, K., & Li, Y. (2000). Disclosure of environmental information by Canadian manufacturing companies: a voluntary disclosure perspective. *Advances in environmental accounting and management*, *1*(1), 201-226.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of econometrics*, *87*(1), 115-143.

BNEF. (2016). Market sizing tool, BNEF

Boopen, S., and Vinesh, S. (2010). On the Relationship between CO2 Emissions and Economic Growth: The Mauritian Experience. *University of Mauritius*.

Bosseboeuf, D., Chateau, B., & Lapillonne, B. (1997). Cross-country comparison on energy efficiency indicators: the on-going European effort towards a common methodology. *Energy Policy*, *25*(7), 673-682.

Boyd, G. A., & Pang, J. X. (2000). Estimating the linkage between energy efficiency and productivity. *Energy Policy, 28*(5), 289-296. doi: http://dx.doi.org/10.1016/S0301-4215(00)00016-1

Boyle, G. (2004). Renewable Energy. *Oxford University Press*.

Bravo-Ureta, B. E., Solís, D., López, V. H. M., Maripani, J. F., Thiam, A., & Rivas, T. (2007). Technical efficiency in farming: a meta-regression analysis. *Journal of productivity Analysis*, *27*(1), 57-72.

Brooks, C. (2019). *Introductory econometrics for finance*: Cambridge university press.

Camagni, R., Capello, R., & Nijkamp, P. (1998). Towards sustainable city policy: an economy-environment technology nexus. *Ecological economics, 24*(1), 103 - 118.

Carraro, C., & Siniscalco., D. . (1992). Environmental Innovation Policy and International Competition. *Environmental and Resource Economics, 2*(2), 183-200.

Caves, D. W., Christensen, L. R., & Diewert, W. E. (1982). The Economic Theory of Index Numbers and the Measurement of Input, Output and Productivity. *Econometrica, 50*, 1393-1414.

Chang, M.-C. (2013). A comment on the calculation of the total-factor energy efficiency (TFEE) index. *Energy Policy, 53*, 500-504. doi: http://dx.doi.org/10.1016/j.enpol.2012.10.025

Chang, T.-P., & Hu, J.-L. . (2010). Total-factor energy productivity growth, technical progress, and efficiency change: An empirical study of China. *Applied Energy, 87*(10), 3262-3270. doi: http://dx.doi.org/10.1016/j.apenergy.2010.04.026

Chang, T.-P., & Hu, J.-L. (2010). Total-factor energy productivity growth, technical progress, and efficiency change: An empirical study of China. *Applied Energy, 87*(10), 3262-3270. doi: http://dx.doi.org/10.1016/j.apenergy.2010.04.026

Charnes, A., & Cooper, W. W. (1962). Programming with linear fractional functionals. *Naval Research Logistics Quarterly 9*(3-4), 181 - 186. doi: 10.1002/nav.3800090303

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the Efficiency of Decision-Making Units. [10.1016/0377-2217(78)90138-8]. *European Journal of Operations Research, 2*, 429-444.

Chen, Y. (2003). A non-radial Malmquist productivity index with an illustrative application to Chinese major industries. *International Journal of Production Economics, 83*(1), 27-35. doi: http://dx.doi.org/10.1016/S0925-5273(02)00267-0

Cherchye, L., Rock, B. D., & Walheer, B. (2015). Multi-output efficiency with good and bad outputs. *European Journal of Operational Research, 240*(3), 872-881. doi: http://dx.doi.org/10.1016/j.ejor.2014.07.028

Chien, T., & Hu, J.-L. (2007). Renewable energy and macroeconomic efficiency of OECD and non-OECD economies. *Energy Policy, 35*(7), 3606-3615. doi: http://dx.doi.org/10.1016/j.enpol.2006.12.033

Chiu, C.-R., Liou, J.-L., Wu, P.-I., & Fang, C.-L. (2012). Decomposition of the environmental inefficiency of the meta-frontier with undesirable output. *Energy Economics, 34*(5), 1392-1399. doi: http://dx.doi.org/10.1016/j.eneco.2012.06.003

Cho, C. H. (2009). Legitimation strategies used in response to environmental disaster: A French case study of Total SA's Erika and AZF incidents. *European Accounting Review,, 18*(1), 33-62.

Cho, C. H., & Patten, D. M. . (2007). The role of environmental disclosures as tools of legitimacy: A research note. *Accounting, organizations and society, 32*(7), 639-647.

Cho, C. H., Guidry, R. P., Hageman, A. M. & Patten, D. M. . (2012). Do actions speak louder than words? An empirical investigation of corporate environmental reputation. . *Accounting, Organizations and Society, 37*, 14-25.

Chontanawat, J., Hunt, L. C., & Pierse, R. (2008). Does energy consumption cause economic growth?: Evidence from a systematic study of over 100 countries. *Journal of Policy Modeling, 30*(2), 209-220. doi: http://dx.doi.org/10.1016/j.jpolmod.2006.10.003

Clark, E., Radić, N., & Sharipova, A. (2018). Bank competition and stability in the CIS markets. *Journal of International Financial Markets, Institutions Money 54*, 190-203.

Clarkson, P. M., Fang, X., Li, Y., & Richardson, G. (2013). The relevance of environmental disclosures: Are such disclosures incrementally informative? *ournal of Accounting and Public Policy, 32*(5), 410-431.

Clarkson, P. M., Li, Y., Richardson, G. D., & Vasvari, F. P. . (2008). Revisiting the relation between environmental performance and environmental disclosure: An empirical analysis. *Accounting, organizations and society, 33*(4), 303-327.

Cleveland, C. J., Costanza, R., Hall, C. A., & Kaufmann, R. . (1997). Energy and the US Economy: A Biophysical Perspective. *INTERNATIONAL LIBRARY OF CRITICAL WRITINGS IN ECONOMICS, 75*, 295-302.

Cole , M. A., & Elliot, R. R. . (2003b). Do environmental regulations influence trade patterns? Testing old and new trade theories. *The World Economy, 26*(8), 1163-1186.

Cole, M. A., & Elliott, R. J. . (2005). FDI and the Capital Intensity of 'Dirty' Sectors: A Missing Piece of the Pollution Haven Puzzle. *Review of Development Economics, 9*(4), 530-548.

Cole, M. A., & Elliott, R. R. . (2002). FDI and the Capital Intensity of „Dirty‟ Sectors:A Missing Piece of the Pollution Haven Puzzle. *University of Birmingham Disscusion Paper in Economics*.

Cole, M. A., Elliot, R. R., & Shimamoto, K. . (2003). US Specialization in Pollution-Intensive Industries: Factor Intensities versus Environmental Regulations. *University of Manchester: School of Economics Studies.*

Colonbo, U. (1992). Development and the global environment. In:Hollander, J.M. (Ed.), The Energy-Environment Connection. 3-14.

COM, C. P. (2000). Towards a European strategy for the security of energy supply. *796 final*.

Cook, W. D., Tone, K., & Zhu, J. (2014). Data envelopment analysis: Prior to choosing a model. *Omega, 44*(0), 1-4. doi: http://dx.doi.org/10.1016/j.omega.2013.09.004

Cook, W. D., & Zhu, J. (2005). Data Envelopment Analysis *Modeling Performance Measurement* (pp. 1-27): Springer US.

Cooper, W. W., Seiford, L. M., & Zhu, J. (2011). Data Envelopment Analysis: History, Models, and Interpretations, Handbook on Data Envelopment Analysis. In W. W. Cooper, L. M. Seiford & J. Zhu (Eds.), (Vol. 164, pp. 1-39): Springer US.

Copeland, B. R., & Taylor, M. S. . (1995). Trade and environment: a partial synthesis. *American Journal of Agricultural Economics, 77*, 765-771.

Creswell, J. W. (2012). Educational Research:Planning,Conducting and Evaluating Quantitative and Qualitative Research.

Creswell, J. W. (2013). *Research design: Qualitative, quantitative, and mixed methods approaches*: Sage publications.

Cummins, J. D., Rubio-Misas, M., & Vencappa, D. (2017). Competition, efficiency and soundness in European life insurance markets. *Journal of Financial Stability, 28*, 66-78.

De Melo, J., & Mathys, N. A. (2010). Trade and Climate Change: The challenges ahead. *CEPR Discussion Paper Series 3083.*

de Villiers, C., & Van Staden, C. J. . (2006). Can less environmental disclosure have a legitimising effect? Evidence from Africa. *Accounting, Organizations and Society, 31*(8), 763-781.

de Villiers, C. M., A. . (2016). Corporate social responsibility, country-level predispositions, and the consequences of choosing a level of disclosure. *Accounting and Business Research, 46*(2), 167-195.

Debreu, G. (1951). The Coefficient of Resource Utilization. *Econometrica, 19*(3), 273-292.

Deegan, C. (2006). Legitimacy theory. *Methodological issues in accounting research: theories and methods*, 161-182.

Demirbaş, A. (2001). Biomass resource facilities and biomass conversion processing for fuels and chemicals. *Energy conversion and Management, 42*(11), 1357-1378.

Dincer, I. (2000). Renewable energy and sustainable development: a crucial review. *Renewable and sustainable energy reviews, 4*(2), 157-175.

Dinda, S. (2004). Environmental Kuznets Curve Hypothesis : A Survey. *Ecological Economics, 49*, 431-455.

Du, K., Worthington, A. C., & Zelenyuk, V. (2018). Data envelopment analysis, truncated regression and double-bootstrap for panel data with application to Chinese banking. *European Journal of Operational Research, 265*(2), 748-764.

ECN, E. R. C. o. t. N. (2011). “Renewable Energy Projections asPublished in the National Renewable Energy Action Plans of the European Member States”, Report for the European Environment Agency.

Ederington, J., & Minier, J. (2003). Is Environmental Policy a Secondary Trade Barrier? An empirical Analysis. *Canadian Journal of Economics, 36*(1), 137-154.

Ederington, J., Levinson, A., & Minier, J. . (2005). Footloose and Pollution Free. *Review of Economics and Statistics, 87*(1), 92-99.

Ekins, P. (1997). The Kuznets Curve for the environment and economic growth: examining the evidence. *Environment and Planning A, 29*, 805-830.

Ellabban, O., Abu-Rub, H., & Blaabjerg, F. (2014). Renewable energy resources: Current status, future prospects, and their enabling technology. *Renewable and Sustainable Energy Reviews, 39*, 748-764.

Eller, S. L., Hartley, P. R., & Medlock, K. B. (2011). Empirical evidence on the operational efficiency of National Oil Companies. *Empirical Economics, 40*(3), 623-643.

Eyre, N. (1997). External costs. What do they mean for energy policy?. *Energy Policy 25*(1), 85-95.

Fang, C.-Y., Hu, J.-L., & Lou, T.-K. (2013). Environment-adjusted total-factor energy efficiency of Taiwan's service sectors. *Energy Policy, 63*(0), 1160-1168. doi: http://dx.doi.org/10.1016/j.enpol.2013.07.124

Fare, R., Grosskopf, S., Lindgren, B., & Roos, P. (1992). Productivity changes in Swedish pharmacies 1980–1989: A non-parametric Malmquist approach. *Journal of Productivity Analysis 3*, 85-101.

Färe, R., Grosskopf, S., & Lovell, C. A. K. (1994). *Production frontiers*. Cambridge [England] ; New York, NY, USA: Cambridge University Press.

Fare, R., Grosskopf, S., Lovell, C. A. K., & Pasurka, C. (1989). Multilateral Productivity Comparisons When Some Outputs Are Undesirable - a Nonparametric Approach. *Review of Economics and Statistics, 71*(1), 90-98.

Farrell, M. J. (1957a). The measurement of productive efficiency. [10.2307/2343100]. *Journal of the Royal Statistical Society, Series A, 120*, 253-290.

Farrell, M. J. (1957b). The Measurement of Productive Efficiency. *Journal of the Royal Statistical Society. Series A (General), 120*(3), 253-290.

Fried, H. O., Lovell, C. A. K., & Schmidt, S. S. (2008). *The measurement of productive efficiency and productivity growth*. New York: Oxford University Press.

Gómez-Calvet, R., Conesa, D., Gómez-Calvet, A. R., & Tortosa-Ausina, E. (2014). Energy efficiency in the European Union: What can be learned from the joint application of directional distance functions and slacks-based measures? *Applied Energy, 132*(0), 137-154. doi: http://dx.doi.org/10.1016/j.apenergy.2014.06.053

Gujarati, D. N. (2009). *Basic econometrics*: Tata McGraw-Hill Education.

Guo, P., Qi, X., Zhou, X., & Li, W. (2018). Total-factor energy efficiency of coal consumption: An empirical analysis of China's energy intensive industries. *Journal of Cleaner Production 172* 2618-2624.

Hahn, T., Pinkse, J., Preuss, L., & Figge, F. . (2015). Tensions in corporate sustainability: Towards an integrative framework. *Journal of Business Ethics, 127*(2), 297-316.

Halkos, G., & Petrou, K. N. (2019). Assessing 28 EU member states' environmental efficiency in national waste generation with DEA. *Journal of Cleaner Production, 208* 509-521.

Hartley, P. R., & Medlock, K. B. (2012). *Changes in the operational efficiency of national oil companies*: University of Western Australia, Business School, Economics.

Hasseldine, J., Salama, A., & Toms, J. . (2005). Quantity versus quality: the impact of environmental disclosures on the reputations of UK Plcs. *The British Accounting Review, 37*, 231-248.

Hayami, Y. (1969). Sources of agricultural productivity gap among selected countries. *The American Journal of Agricultural Economics, 51*, 564-575.

Hayami, Y., & Ruttan, V. W. (1970). Agricultural Productivity Differences among Countries. *The American Economic Review, 60*(5), 895-911.

He, F., Zhang, Q., Lei, J., Fu, W., & Xu, X. (2013). Energy efficiency and productivity change of China’s iron and steel industry: Accounting for undesirable outputs. *Energy Policy, 54*, 204-213. doi: http://dx.doi.org/10.1016/j.enpol.2012.11.020

Healy, P. M., & Palepu, K. G. . (2001). Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of accounting and economics, 31*(1), 405-440.

Herring, H. (1996). Is energy efficiency good for the environment: some conflicts and confusions. *The UK energy experience: a model or a warning. Imperial College Press, London, 327*, 338.

Hettige, H., Dasgupta, S., & Wheeler, D. . (2000). What improves environmental compliance? Evidence from Mexican industry. *Journal of Environmental Economics and Management, 39*(1), 39-66.

Hoff, A. (2007). Second stage DEA: Comparison of approaches for modelling the DEA score. *European Journal of Operational Research, 181*(1), 425-435. doi: http://dx.doi.org/10.1016/j.ejor.2006.05.019

Honma, S., & Hu, J.-L. (2009). Total-factor energy productivity growth of regions in Japan. *Energy Policy, 37*(10), 3941-3950. doi: http://dx.doi.org/10.1016/j.enpol.2009.04.034

Honma, S., & Hu, J.-L. (2008). Total-factor energy efficiency of regions in Japan. *Energy Policy, 36*(2), 821-833. doi: http://dx.doi.org/10.1016/j.enpol.2007.10.026

Honma, S., & Hu, J.-L. (2009). Total-factor energy productivity growth of regions in Japan. *Energy Policy, 37*(10), 3941-3950. doi: http://dx.doi.org/10.1016/j.enpol.2009.04.034

Honma, S., & Hu, J.-L. (2014a). Industry-level total-factor energy efficiency in developed countries: A Japan-centered analysis. *Applied Energy, 119*, 67-78. doi: http://dx.doi.org/10.1016/j.apenergy.2013.12.049

Honma, S., & Hu, J.-L. (2014b). A panel data parametric frontier technique for measuring total-factor energy efficiency: An application to Japanese regions. *Energy, 78*, 732-739. doi: http://dx.doi.org/10.1016/j.energy.2014.10.066

Hsieh, J., Lu , C., Li , Y., Y., C., & Xu, Y. (2019). Environmental Assessment of European Union Countries. *Energies, 12*(2), 295. doi: 10.3390/en12020295

Hu, J.-L., & Kao, C.-H. (2007). Efficient energy-saving targets for APEC economies. *Energy Policy, 35*(1), 373-382. doi: http://dx.doi.org/10.1016/j.enpol.2005.11.032

Hu, J.-L., & Wang, S.-C. (2006). Total-factor energy efficiency of regions in China. *Energy Policy, 34*(17), 3206-3217. doi: http://dx.doi.org/10.1016/j.enpol.2005.06.015

Huang, C. L., & Kung, F. H. . (2010). Drivers of environmental disclosure and stakeholder expectation: Evidence from Taiwan. *Journal of Business Ethics, 96*(3), 435-451.

IEA. (2010). World Energy Outlook 2010, OECD/IEA, Paris.

IEA. (2015). Energy and Climate change *World Energy Outlook*. Paris, France: International Energy Agency.

IEA. (2012). “Energy Technology Perspectives 2012”. *International Energy Agency*.

IEA. (2016). World Energy Outlook 2016.

Iftikhar, Y., Wang, Z., Zhang, B., & Wang, B. (2018). Energy and CO2 emissions efficiency of major economies: A network DEA approach. *Energy 147*, 197-207.

Ike, C. B., & Lee, H. (2014). Measurement of the efficiency and productivity of national oil companies and its determinants. *Geosystem Engineering*, *17*(1), 1-10.

IPCC. (2001). Climate Change 2001: The Scientific Basis. Contribution of Working Group I to the Third Assessment Report of the. (J. T. Houghton, Y. Ding, D. J. Griggs, & M. P. Noguer, Eds.). *United Kingdom and New York: Cambridge University Press*.

IPCC. (2014). Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.Geneva: IPCC *Climate Change*.

IRENA. (2012). Renewable energy technologies: Cost analysis series. . *Concentrating Sol. Power*, *1*(5), 1-56.

IRENA. (2016). Renewable Capacity Statistics 2016, Abu Dhabi.

IRENA. (2016b). Renewable Energy Benefits: Decentralised Solutions in the Agri-food Chain, IRENA, Abu Dhabi.

IRENA. (2017). Accelerating the global energy transformation.

Jacobsson, S., & Bergek, A. (2004). Transforming the energy sector: the evolution of technological systems in renewable energy technology. *Industrial and corporate change*, *13*(5), 815-849.

Jebali, E., Essid, H., Khraief, N. (2017). The analysis of energy efficiency of the Mediterranean countries: a two-stage double bootstrap DEA approach *Energy*, *134*, 991-1000.

JRC. (2016). "Emission Database for Global Atmospheric Research (EDGAR)", CO2 time series 1990-2014 per region/country.

Kamal, Y. D., C. . (2013). Corporate Social and Environment-related Governance Disclosure Practices in the Textile and Garment Industry: Evidence from a Developing Country. *Australian accounting review*, *23*(2), 117-134.

Kashani, H. A. (2005). State intervention causing inefficiency: an empirical analysis of the Norwegian Continental Shelf. *Energy Policy, 33*(15), 1998-2009.

Keho, Y. (2016). What drives energy consumption in developing countries? The experience of selected African countries. *Energy Policy 91*, 233-246. doi: https://doi.org/10.1016/j.enpol.2016.01.010

Kenjegalieva, K. A., Simper, R., & Weyman-Jones, T. G. (2009). Efficiency of transition banks: inter-country banking industry trends. *Applied Financial Economics, 19*(19), 1531-1546.

Kennedy, P. (2008). A guide to econometrics. . *Malden, MA: Blackwell*.

Koetter, M., Kolari, J., & Spierdijk, L. (2008). *Efficient competition? Testing the 'quiet life'of US banks with adjusted Lerner indices.* Paper presented at the Proceedings 44th Bank Structure and Competition Conference, Federal Reserve Bank of Chicago.

Koopmans, T. C. (1951). An analysis of production as an efficient combination of activities. In T. C. Koopmans (Ed.), *Activity analysis of production and allocation*. New York: Cowles Commission for Research in Economics, Monograph No. 13, Wiley.

Koskimäki, P.-L. (2012). Africa could take a leap to energy efficiency: What lessons could Sub-Saharan countries learn from European energy efficiency policy implementation? *Energy for Sustainable Development, 16*(2), 189-196. doi: http://dx.doi.org/10.1016/j.esd.2011.12.004

Kounetas, K., & Zervopoulos, P. D. (2019). A cross-country evaluation of environmental performance: Is there a convergence-divergence pattern in technology gaps? *European Journal of Operational Research 273*, 1136–1148.

Kumar, S. (2006). Environmentally sensitive productivity growth: A global analysis using Malmquist–Luenberger index. *Ecological Economics, 56*(2), 280-293. doi: http://dx.doi.org/10.1016/j.ecolecon.2005.02.004

Kuosmanen, T., & Kortelainen, M. (2007). *Stochastic Nonparametric Envelopment of Data: Crosssectional Frontier Estimation Subject to Shape Constraints*. Discussion Paper No. 46. University of Joensuu, Economics.

L.M. Seiford, J. Z. (2002). Modeling undesirables factors in efficiency evaluation. *Economics Letters, 28*, 16–20.

Larson, M. G. (2006). Descriptive statistics and graphical displays. *Circulation, 114*(1), 76-81.

Levinson, A. (2009). Technology, International Trade, and Pollution from US Manufacturing. *American Economic Review*.

Li, K., & Lin, B. (2015). Metafroniter energy efficiency with CO2 emissions and its convergence analysis for China. *Energy Economics, 48,* 230-241. doi: http://dx.doi.org/10.1016/j.eneco.2015.01.006

Li, L.-B., & Hu, J.-L. (2012). Ecological total-factor energy efficiency of regions in China. *Energy Policy, 46*, 216-224. doi: http://dx.doi.org/10.1016/j.enpol.2012.03.053

Li, Q. (1996). Nonparametric testing of closeness between two unknown distribution functions. *Econometric Reviews, 15*(3), 261-274.

Li, Z., Crook, J., & Andreeva, G. (2014). Chinese companies distress prediction: an application of data envelopment analysis. [Special Issue Paper]. *J Oper Res Soc, 65*(3), 466-479. doi: 10.1057/jors.2013.67

Lightstone, K., & Driscoll, C. (2008). Disclosing elements of disclosure: a test of legitimacy theory and company ethics. *Canadian Journal of Administrative Sciences, 25*(1), 7.

Lin, B., & Du, K. (2013). Technology gap and China's regional energy efficiency: A parametric metafrontier approach. *Energy Economics, 40,* 529-536. doi: http://dx.doi.org/10.1016/j.eneco.2013.08.013

Lin, B., & Du, K. (2014). Measuring energy efficiency under heterogeneous technologies using a latent class stochastic frontier approach: An application to Chinese energy economy. *Energy, 76*, 884-890. doi: http://dx.doi.org/10.1016/j.energy.2014.08.089

Lin, B., & Wang, X. (2014). Exploring energy efficiency in China׳s iron and steel industry: A stochastic frontier approach. *Energy Policy, 72,* 87-96. doi: http://dx.doi.org/10.1016/j.enpol.2014.04.043

Lovell, C. A. K., & Pastor, J. T. (1995). Units invariant and translation invariant DEA models. [doi: 10.1016/0167-6377(95)00044-5]. *Operations Research Letters, 18*(3), 147-151.

Lu, W.-M., Wang, W.-K., & Kweh, Q. L. (2014). Intellectual capital and performance in the Chinese life insurance industry. *Omega, 42*(1), 65-74.

Luhnen, M. (2009). Determinants of efficiency and productivity in German property-liability insurance: evidence for 1995–2006. *The Geneva Papers on Risk and Insurance-Issues and Practice, 34*(3), 483-505.

Lv, W., Hong, X., & Fang, K. (2015). Chinese regional energy efficiency change and its determinants analysis: Malmquist index and Tobit model. [Article]. *Annals of Operations Research, 228*(1), 9-22. doi: 10.1007/s10479-012-1094-5

Lys, T., Naughton, J. P., & Wang, C. . (2015). Signaling through corporate accountability reporting. *Journal of Accounting and Economics, 60*(1), 56-72.

Magness, V. (2006). Strategic posture, financial performance and environmental disclosure: an empirical test of legitimacy theory. *Accounting, Auditing & Accountability Journal, 19*(4), 540-563.

Mahlberg, B., & Url, T. (2010). Single Market effects on productivity in the German insurance industry. *Journal of Banking & Finance, 34*(7), 1540-1548. doi: http://dx.doi.org/10.1016/j.jbankfin.2009.09.005

Mahoney, L. S., Thorne, L., Cecil, L., & LaGore, W. . (2013). A research note on standalone corporate social responsibility reports: Signaling or greenwashing? . *Critical perspectives on Accounting, 24*(4), 350-359.

Mallon, K. (2006). Renewable Energy Policy and Politics. *Earthscan*.

Malmquist, S. (1953). Index Numbers and Indifference Surfaces. *Trabajos de Estadistica 4*, 209–242.

Mandelli, S. (2014). “Sustainable Energy in Africa: A Comprehensive Data and Policies Review”. *Renewable and Sustainable Energy Reviews, 37*, 656-686.

McDonald, J. (2009). Using least squares and tobit in second stage DEA efficiency analyses. *European Journal of Operational Research, 197*(2), 792-798. doi: DOI: 10.1016/j.ejor.2008.07.039

Moncef Krartia, K. D. (2018). Review analysis of economic and environmental benefits of improving energy efficiency for UAE building stock. *Renewable and Sustainable Energy Reviews 82* 14–24.

Mukherjee, K. (2010). Measuring energy efficiency in the context of an emerging economy: The case of indian manufacturing. *European Journal of Operational Research, 201*(3), 933-941. doi: DOI: 10.1016/j.ejor.2009.04.012

Murillo-Zamorano, L. R. (2004). Economic efficiency and frontier techniques. *Journal of Economic Surveys, 18*(1), 33-77.

Murillo-Zamorano, L. R., & Vega-Cervera, J. A. (2001). The use of parametric and non-parametric frontier methods to measure the productive efficiency in the industrial sector: A comparative study. *International Journal of Production Economics, 69*(3), 265-275. doi: http://dx.doi.org/10.1016/S0925-5273(00)00027-X

Murphy, D. J., & Hall, C. A. (2011). Energy return on investment, peak oil, and the end of economic growth. [Review]. *Ann N Y Acad Sci, 1219*(1), 52-72. doi: 10.1111/j.1749-6632.2010.05940.x

Narayan, P. K., & Smith, R. (2008). Energy consumption and real GDP in G7 countries,new evidence from panel cointegration with structural breaks *EnergyEcon 30*, 2331–2341.

O'Donnell, C., Rao, D., & Battese, G. (2008). Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. *Empirical Economics, 34*(2), 231-255. doi: 10.1007/s00181-007-0119-4

O'Donnell, C., Rao, D. S. P., & Battese, G. (2008). Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. *Empirical Economics, 34*(2), 231-255. doi: 10.1007/s00181-007-0119-4

O'Donnell, C. J., Rao, D. P., & Battese, G. E. (2008). Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. *Empirical Economics, 34*(2), 231-255.

O'Donovan, G. (2002). Environmental disclosures in the annual report: Extending the applicability and predictive power of legitimacy theory. *Accounting, Auditing & Accountability Journal, 15*(3), 344-371.

Odeck, J. (2007). Measuring technical efficiency and Productivity growth: a comparison of SFA and DEA on Norwegian grain production data *Applied Economics, 39*(20), 2617-2630. doi: 10.1080/00036840600722224

Odhiambo, N. M. (2009). Energy consumption and economic growth nexus in tanzania: an ARDL bounds testing approach *EnergyPolicy 37*(2), 617–622.

Oh, D.-h., & Lee, J.-d. (2010). A metafrontier approach for measuring Malmquist productivity index. *Empirical Economics, 38*(1), 47-64. doi: 10.1007/s00181-009-0255-0

Oh, W., & Lee, K. (2004). Energy consumption and economic growth in Korea: testing the causality relation. *Journal of Policy Modeling, 26*(8–9), 973-981. doi: http://dx.doi.org/10.1016/j.jpolmod.2004.06.003

Ohene-Asare, K., & Turkson, C. (2018). Total-Factor Energy Efficiency and Productivity of ECOWAS States: A Slacks-Based Measure with Undesirable Outputs. *Journal of African Business*, 1-21. doi: 10.1080/15228916.2018.1480248

P. Zhou, B. W. A. (2008). Linear programming models for measuring economy-wide energy efficiency performance. *Energy Policy*, *36*, 2911–2916.

P. Zhou, B. W. A., K.L. Poh. (2008). Measuring environmental performance under different environmental DEA technologies. *Energy Economics*, *30*, 1-14.

Pao, H.-T., & Tsai, C.-M. (2010). CO2 emissions, energy consumption and economic growth in BRIC countries. *Energy Policy*, *38*(12), 7850-7860. doi: http://dx.doi.org/10.1016/j.enpol.2010.08.045

Pao, H.-T., & Tsai, C.-M. (2011). Multivariate Granger causality between CO2 emissions, energy consumption, FDI (foreign direct investment) and GDP (gross domestic product): Evidence from a panel of BRIC (Brazil, Russian Federation, India, and China) countries. *Energy*, *36*(1), 685-693. doi: http://dx.doi.org/10.1016/j.energy.2010.09.041

Pastor, J. (1996). Translation invariance in data envelopment analysis: A generalization. *Annals of Operations Research*, *66*(2), 91-102. doi: 10.1007/bf02187295

Patterson, M. G. (1996). What is energy efficiency?: Concepts, indicators and methodological issues. *Energy Policy*, *24*(5), 377-390. doi: http://dx.doi.org/10.1016/0301-4215(96)00017-1

Patterson, M. G. (1996). What is energy efficiency?: Concepts, indicators and methodological issues. *Energy Policy*, *24*(5), 377-3390. doi: http://dx.doi.org/10.1016/0301-4215(96)00017-1

Pearce, D., & Warford, J. (1993). World without end: economics, environment and sustainable development. *Oxford University Press, Oxford*.

Pittman, R. W. (1983). Multilateral productivity comparisons with undesirable outputs. *Economic Journal 93*, 883–891.

Plumlee, M., Brown, D., Hayes, R. M., & Marshall, R. S. . (2015). Voluntary environmental disclosure quality and firm value: Further evidence. *Journal of Accounting and Public Policy*, *34*(4), 336-361.

Ramachandra, T., Loerincik, Y., & Shruthi, B. (2006). Intra-and Inter-Country Energy Intensity Trends. *JOURNAL OF ENERGY AND DEVELOPMENT*, *31*(1), 43.

Ramanathan, R. (2005). An analysis of energy consumption and carbon dioxide emissions in countries of the Middle East and North Africa. *Energy, 30*(15), 2831-2842. doi: http://dx.doi.org/10.1016/j.energy.2005.01.010

Rao, X., Wu, J., Zhang, Z., & Liu, B. (2012). Energy efficiency and energy saving potential in China: An analysis based on slacks-based measure model. *Computers & Industrial Engineering, 63*(3), 578-584. doi: http://dx.doi.org/10.1016/j.cie.2011.08.023

Ray, S. C., Seiford, L. M., & Zhu, J. (1998). Market entity behavior of Chinese state-owned enterprises. *Omega, 26*(2), 263-278. doi: http://dx.doi.org/10.1016/S0305-0483(97)00044-3

Ritchie, H., & Roser, M. (2018). CO2 and other Greenhouse Gas Emissions.

Roberts, M. R., & Whited, T. M. (2013). Endogeneity in empirical corporate finance1 *Handbook of the Economics of Finance* (Vol. 2, pp. 493-572): Elsevier.

Rothman, D. S. (1998). Environmental Kuznets Curve - real progress or passing the buck?: a case for consumption-base approaches. *Ecological Economics, 25*, 177-194.

Ruggiero, J., & Vitaliano, D. F. (1999). Assessing the efficiency of public schools using data envelopment analysis and frontier regression. *Contemporary Economic Policy, 17*(3), 321-331.

Sadorsky, P. (2010). The impact of financial development on energy consumption in emerging economies. *Energy Policy, 38*(5), 2528–2535.

Sanglimsuwan, K. (2011). Carbon Dioxide Emissions and Economic Growth: An Econometric Analysis. *International Research Journal of Finance and Economics*(67).

Sawin, J. L., Sverrisson, F., Seyboth, K., Adib, R., Murdock, H. E., & Lins, C. S., K. . (2013). Renewables 2017 Global Status Report.

Shehata, N. F. (2014). Theories and determinants of voluntary disclosure. *Accounting and Finance Research (AFR), 3*(1).

Shen, P., He, Y., Guo, X., 2017. . . (2017). The impacts of urbanization on energy consumption and efficiency. *Energy Environment, 28*(7), 673-686.

Shephard, R. W. (1970). *Theory of Cost and Production Functions* Princeton: Princeton University Press.

Shi, P., & Frees, E. W. (2010). Long-tail longitudinal modeling of insurance company expenses. *Insurance: Mathematics and Economics*, *47*(3), 303-314. doi: http://dx.doi.org/10.1016/j.insmatheco.2010.07.005

Show, K. Y. (2010). Green Technology.

Simar, L. (2007). How to improve the performances of DEA/FDH estimators in the presence of noise? [10.1007/s11123-007-0057-3]. *Journal of Productivity Analysis*, *28*(3), 183-201.

Simar, L., & Wilson, P. W. (1998). Sensitivity Analysis of Efficiency Scores: How to Bootstrap in Nonparametric Frontier Models. *Management Science*, *44*(1), 49-61. doi: 10.1287/mnsc.44.1.49

Simar, L., & Wilson, P. W. (1999). Estimating and bootstrapping Malmquist indices. *European Journal of Operational Research*, *115*(3), 459-471. doi: http://dx.doi.org/10.1016/S0377-2217(97)00450-5

Simar, L., & Wilson, P. W. (2000). A general methodology for bootstrapping in non-parametric frontier models. *Journal of Applied Statistics*, *27*(6), 779 - 802.

Simar, L., & Wilson, P. W. (2002). Non-parametric tests of returns to scale. [doi: DOI: 10.1016/S0377-2217(01)00167-9]. *European Journal of Operational Research*, *139*(1), 115-132.

Simar, L., & Wilson, P. W. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics*, *136*(1), 31-64. doi: DOI: 10.1016/j.jeconom.2005.07.009

Simar, L., & Wilson, P. W. (2011). Estimation and Inference in Nonparametric Frontier Models: Recent Developments and Perspectives. *Foundations and Trends in Econometrics*, *5*(3-4), 183-337. doi: 10.1561/0800000020

Simar, L., & Wilson, P. W. (2015). Statistical Approaches for Non-parametric Frontier Models: A Guided Tour. *International Statistical Review*, *83*(1), 77-110.

Simar, L., & Zelenyuk, V. (2006). On testing equality of distributions of technical efficiency scores. *Econometric Reviews*, *25*(4), 497-522.

Singh, J. (2016). Why energy efficiency matters and how to scale it up. *Live wire knowledge note series 1*.

Song, M.-L., Zhang, L.-L., Liu, W., & Fisher, R. (2013). Bootstrap-DEA analysis of BRICS' energy efficiency based on small sample data. *Applied Energy, 112*(0), 1049-1055. doi: http://dx.doi.org/10.1016/j.apenergy.2013.02.064

Song, M.-L., Zhang, L.-L., Liu, W., & Fisher, R. . (2013). Bootstrap-DEA analysis of BRICS' energy efficiency based on small sample data *Applied Energy, 112*(0), 1049-1055. doi: http://dx.doi.org/10.1016/j.apenergy.2013.02.064

Song, M., Yang, L., Wu, J., & Lv, W. (2013). Energy saving in China: Analysis on the energy efficiency via bootstrap-DEA approach. *Energy Policy, 57*, 1-6. doi: http://dx.doi.org/10.1016/j.enpol.2012.11.001

Stern, D. I., Common, M. S., & Barbier, E. B. . (1996). Economic growth and environmental degradation: a critique of the environmental Kuznets curve. *World Development, 24*, 1151-1160.

Stern, N. (2007). *The economics of climate change: the Stern review*. Cambridge and New York: Cambridge University Press.

Stern, N. (2008). The economics of climate change. *The American Economic Review*, 1-37.

Su, B., and Ang, B.W. (2011). Multi-region input–output analysis of CO2 emissions embodied in trade: the feedback effects'. *Ecological Economics 71* 42–53

Sueyoshi, T., & Goto, M. (2012b). Returns to scale and damages to scale under natural and managerial disposability: Strategy, efficiency and competitiveness of petroleum firms. *Energy Economics, 34*(3), 645-662.

Sullivan, R., & Gouldson, A. . (2012). Does voluntary carbon reporting meet investors' needs? *Journal of Cleaner Production, 36*, 60-67.

Thanassoulis, E. (2001). *Introduction of the Theory and Application of Data Envelopment Analysis* (1st ed.). New York: Springer.

Thompson, R. G., Lee, E., & Thrall, R. M. (1992). DEA/AR-efficiency of U.S. independent oil/gas producers over time. *Computers & Operations Research, 19*(5), 377-391. doi: Doi: 10.1016/0305-0548(92)90068-g

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. *European Journal of Operational Research, 130*(3), 498-509. doi: Doi: 10.1016/s0377-2217(99)00407-5

Tortosa-Ausina, E., Armero, C., Conesa, D., & Grifell-Tatjé, E. (2012). Bootstrapping profit change: An application to Spanish banks. *Computers & Operations Research, 39*(8), 1857-1871.

Tortosa-Ausina, E., Grifell-Tatjé, E., Armero, C., & Conesa, D. (2008). Sensitivity analysis of efficiency and Malmquist productivity indices: An application to Spanish savings banks. *European Journal of Operational Research, 184*(3), 1062-1084.

Vestergaard, N., Hoff, A., Andersen, J., Lindebo, E., Grønbæk, L., Pascoe, S., . . . Daures, F. (2002). Measuring capacity in fishing industries using the Data Envelopment Analysis (DEA) approach. *University of Southern Denmark, octubre*.

Vutha, H., and Jalilian, H. . (2008). Environmental Impacts of the ASEAN-China Free Trade Agreement on the Greater Mekong Sub-Region. *Cambodia Development Resource Institute*.

Wang, H., Zhou, P., & Zhou, D. Q. (2013). Scenario-based energy efficiency and productivity in China: A non-radial directional distance function analysis. *Energy Economics, 40*, 795-803. doi: http://dx.doi.org/10.1016/j.eneco.2013.09.030

Wang, K., Lu, B., & Wei, Y. (2013). China's regional energy and environmental efficiency: A Range-Adjusted Measure based analysis. *Applied Energy, 112*(0), 1403-1415. doi: http://dx.doi.org/10.1016/j.apenergy.2013.04.021

Wang, P. Z., D. Zhou (2011). Efficiency measurement with carbon dioxide emissions: the case of China,. *Applied Energy*. doi: doi:10.1016/j.apenergy.2011.02.022

Wang, Y., Duan, F., Ma, X., & He, L. (2019). Carbon emissions efficiency in China: Key facts from regional and industrial sector. *Journal of Cleaner Production, 206* 850-869.

Wang, Z.-H., Zeng, H.-L., Wei, Y.-M., & Zhang, Y.-X. (2012). Regional total factor energy efficiency: An empirical analysis of industrial sector in China. *Applied Energy, 97*, 115-123. doi: http://dx.doi.org/10.1016/j.apenergy.2011.12.071

Wang, Z., Feng, C., & Zhang, B. (2014). An empirical analysis of China's energy efficiency from both static and dynamic perspectives. *Energy, 74*(0), 322-330. doi: http://dx.doi.org/10.1016/j.energy.2014.06.082

Wanke, P., Barros, C. P., & Faria, J. R. (2015). Financial distress drivers in Brazilian banks: A dynamic slacks approach. *European Journal of Operational Research, 240*(1), 258-268. doi: http://dx.doi.org/10.1016/j.ejor.2014.06.044

Wei, B., Yagita, H., Inaba, A., & Sagisaka, M. (2003). Urbanization impact on energy demand and CO2 emission in China. *Journal of Chongqing University, 2*, 46-50. doi: https://doi.org/10.1016/j.enpol.2012.06.048

Williams, J. (2012). Efficiency and market power in Latin American banking. *Journal of Financial Stability, 8*(4), 263-276.

Wolde-Rufael, Y. (2009). Energy consumption and economic growth :the experience of African countries revisited. *EnergyEcon 1* 217–224.

Wolf, C. (2009). Does ownership matter? The performance and efficiency of State Oil vs. Private Oil (1987–2006). *Energy Policy, 37*(7), 2642-2652.

Woo, C., Chung, Y., Chun, D., Seo, H., & Hong, S. (2015). The static and dynamic environmental efficiency of renewable energy: A Malmquist index analysis of OECD countries. *Renewable and Sustainable Energy Reviews, 47*, 367-376. doi: http://dx.doi.org/10.1016/j.rser.2015.03.070

Wooldridge, J. M. (2005). *Introductory Econometrics: A Modern Approach* (3rd ed.): South-Western College Pub.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*: MIT press.

Wooldridge, J. M. (2015). *Introductory econometrics: A modern approach*: Nelson Education.

Wu, T., Chen, Y., Shang, W., & Wu, J. (2018). Measuring energy use and CO2 emission performances for APEC economies. *Journal of Cleaner Production 183*, 590-601.

Wu, Y. (2012). Energy intensity and its determinants in China's regional economies. *Energy Policy, 41*, 703-711. doi: http://dx.doi.org/10.1016/j.enpol.2011.11.034

Xiaoli, Z., Rui, Y., & Qian, M. (2014). China's total factor energy efficiency of provincial industrial sectors. *Energy, 65,* 52-61. doi: http://dx.doi.org/10.1016/j.energy.2013.12.023

Xiaoli, Z., Rui, Y., & Qian, M. (2014). China's total factor energy efficiency of provincial industrial sectors. *Energy Policy, 65*, 52-61. doi: http://dx.doi.org/10.1016/j.energy.2013.12.023

Xing, Y., & Kolstad, C. (1996). Environmental and Trade: A Review of Theory and Issues. *Munich Personal RePEc Archive*.

Y.W. Bian, F. Y., , . (2010). Resource and environment efficiency analysis of provinces in China: A DEA approach based on Shannon's entropy. *Energy Policy, 38* 1909–1917

Yang, Z., & Wei, X. (2019). The measurement and influences of China's urban total factor energy efficiency under environmental pollution: Based on the game cross-efficiency DEA *Cleaner Production 209*, 439-450. doi: https://doi.org/10.1016/j.jclepro.2018.10.271

Yeh, L., Chen, Y., & Lai, P. (2010). A comparative study of energy utilization efficiency between Taiwan and China. *Energy Policy 38* 2386–2394

Yongming Han , C. L., Zhiqiang Geng , Keyu Zhang. (2018). Carbon emission analysis and evaluation of industrial departments in China: An improved environmental DEA cross model based on information entropy. *Journal of Environmental Management, 205*, 298-307.

Zaim, o., & Taskin, F. (2000). Environmental efficiency in carbon dioxide emissions in the OECD: A non-parametric approach. *Journal of Environmental Management 58*, 95–107 doi: 10.1006/jema.1999.0313

Zeng, D. Z., & Zhao, L. . (2009). Pollution Havens and Industrial Agglomeration. *Journal of Environmental Economics and Management, 58*(2), 141-153.

Zhang, N., Kong, F., & Yu, Y. (2015). Measuring ecological total-factor energy efficiency incorporating regional heterogeneities in China. *Ecological Indicators, 51*, 165-172. doi: http://dx.doi.org/10.1016/j.ecolind.2014.07.041

Zhang, X.-P., Cheng, X.-M., Yuan, J.-H., & Gao, X.-J. (2011). Total-factor energy efficiency in developing countries. *Energy Policy, 39*(2), 644-650. doi: http://dx.doi.org/10.1016/j.enpol.2010.10.037

Zhongshan Yang, X. W. (2019). The measurement and influences of China's urban total factor energy efficiency under environmental pollution: Based on the game crossefficiency DEA. *Journal of Cleaner Production 209*, 439-450.

Zhou, P., Ang, B. W., & Poh, K. L. (2008). A survey of data envelopment analysis in energy and environmental studies. *European Journal of Operational Research, 189*(1), 1-18. doi: http://dx.doi.org/10.1016/j.ejor.2007.04.042

Zhou, P., Ang, B. W., & Zhou, D. Q. (2012). Measuring economy-wide energy efficiency performance: A parametric frontier approach. *Applied Energy, 90*(1), 196-200. doi: http://dx.doi.org/10.1016/j.apenergy.2011.02.025

Zhou, P., Poh, K. L., & Ang, B. W. (2007). A non-radial DEA approach to measuring environmental performance. *European Journal of Operational Research*, *178*(1), 1-9. doi: http://dx.doi.org/10.1016/j.ejor.2006.04.038

Zhongshan Yang, X. W. (2019). The measurement and influences of China's urban total factor energy efficiency under environmental pollution: Based on the game cross efficiencyDEA. *Journal of Cleaner Production 209*, 439-450.

Zhu, J. (1996). Robustness of the efficient DMUs in data envelopment analysis. *European Journal of Operational Research*, *90*(3), 451-460. doi: http://dx.doi.org/10.1016/0377-2217(95)00054-2

Zhu, J. (2015). Data Envelopment Analysis; A Handbook of Models and Methods Vol. 221. doi:10.1007/978-1-4899-7553-9

Zhu, L., & Chen, J. (2019). A dynamic approach to energy efficiency estimation in the large-scale chemical plant. *Cleaner Production*, *212*, 1072-1085. doi: https://doi.org/10.1016/j.jclepro.2018.11.186

Zou, G., Chen, L., Liu, W., Hong, X., Zhang, G., & Zhang, Z. (2013). Measurement and evaluation of Chinese regional energy efficiency based on provincial panel data. *Mathematical and Computer Modelling*, *58*(5–6), 1000-1009. doi: http://dx.doi.org/10.1016/j.mcm.2012.09.020

Zuckerman, S., Welch, W. P., & Pope, G. C. (1990). A geographic index of physician practice costs. [Research Support, U.S. Gov't, Non-P.H.S.]. *J Health Econ*, *9*(1), 39-69. doi: http://dx.doi.org/10.1016/0167-6296(90)90040-A

APPENDICES

APPENDIX A

ANOVA - Capital Stock (year by year)

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	9.54E+24	1	9.54E+24	152.6161	2.01E-34	3.843831
Within Groups	2.45E+26	3922	6.25E+22			

ANOVA-Labor (year by year)

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	4.79E+17	1	4.79E+17	152.2238	2.44E-34	3.843831
Within Groups	1.23E+19	3922	3.14E+15			

ANOVA – energy (year by year
)

Source of Variation	*SS*	*Df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	1.71E+08	1	1.71E+08	49.45487	2.38E-12	3.843831
Within Groups	1.36E+10	3922	3459637			

ANOVA - CO2 (year by
year)

Source of Variation	*SS*	*Df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	4.63E+13	1	4.63E+13	135.6155	7.75E-31	3.843831

Within Groups	1.34E+15	3922	3.42E+11			

ANOVA- CH_4 (year by year)

Source of Variation	*SS*	*Df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	2.6E+12	1	2.6E+12	218.0785	4.54E-48	3.843831
Within Groups	4.68E+13	3922	1.19E+10			

ANOVA – N_2O (year by year)

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	3.57E+11	1	3.57E+11	211.6364	9.76E-47	3.843831
Within Groups	6.62E+12	3922	1.69E+09			

ANOVA GDP (year by year)

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	1.19E+11	1	1.19E+11	736.2437	9.8E-149	3.843831
Within Groups	6.31E+11	3922	1.61E+08			

APPENDIX B

Summary Statistics of Input and Outputs by Continental Groupings

Continental Groupings	Variables	Mean	Std. Dev.	Min	Max	Count
	Capital	10772930245.00	39824326393.00	74285.93	762867000000.00	424
	Labor	9240902.00	9961277.00	143256.00	54260696.00	424
	Energy	783.05	766.96	56.93	4925.11	42
AFR	GDP	2395.32	3331.29	153.70	45699.20	424
	CO2	39090.21	95484.63	102.68	780565.00	424
	CH4	22661.89	26855.12	240.10	189678.00	424
	N2O	12259.93	18950.54	35.46	149775.00	424
		Mean	**Std. Dev.**	**Min**	**Max**	**Count**
	Capital	145141461609.48	473013206290.34	377543.97	4721377102256.08	476
	Labor	56161279.15	152036300.19	157080.00	786573327.00	476
	Energy	2836.11	3079.03	138.79	12087.10	476
ASIA	GDP	10418.94	13852.10	138.44	56957.08	476
	CO2	413682.13	1307054.48	1881.17	10291926.88	476
	CH4	103346.26	268575.65	904.60	1752290.14	476
	N2O	34477.50	94648.86	91.14	587166.37	476
		Mean	**Std. Dev.**	**Min**	**Max**	**Count**
	Capital	136337035640.78	139070539242.34	10972203925.70	437053452344.31	30
	Labor	6606954.67	4511220.73	1928886.00	12355521.00	30
	Energy	5009.08	735.67	4054.50	5973.86	30
AUS	GDP	35615.98	15447.95	13640.99	67990.29	30
	CO2	198329.70	168490.33	31503.20	394792.89	30
	CH4	77195.15	50359.68	26583.90	136147.00	30
	N20	37803.25	26985.88	11320.30	81507.99	30
		Mean	**Std. Dev.**	**Min**	**Max**	**Count**
	Capital	90017247809.98	149117197856.55	198859523.54	778202309427.54	629
	Labor	9264727.58	14242120.27	156205.00	76961789.00	629
	Energy	3402.78	2397.63	352.00	18178.14	629
EUR	GDP	24133.86	22838.96	354.00	119225.38	629
	CO2	152507.43	286198.61	1800.50	1830830.42	629
	CH4	31342.15	78623.55	140.94	545818.58	629
	N2O	11326.08	15957.42	60.82	119441.45	629
		Mean	**Std. Dev.**	**Min**	**Max**	**Count**
	Capital	240635374975.60	731189910501.94	27568.89	3432772000000.00	212
	labor	17704037.58	39549866.76	106027.00	159800262.00	212
	Energy	2629.57	3634.94	235.14	15109.19	212

NAM	**GDP**	10519.81	14101.97	329.78	54696.73	212
	CO2	471349.50	1406920.51	392.37	5789727.29	212
	CH4	57467.61	136570.83	99.50	556609.00	212
	N2O	29333.02	78319.51	55.04	325500.00	212
		Mean	**Std. Dev.**	**Min**	**Max**	**Count**
	Capital	43270000000.00	90650000000.00	110261364.00	539200000000.00	184
	Labor	14926803.66	24157836.07	163650.00	100603554.00	184
	Energy	1222.05	623.54	432.03	3499.31	184
SAM	**GDP**	5676.29	3945.67	913.58	16881.21	184
	CO2	80741.60	110613.00	1290.78	529808.20	184
	CH4	61980.61	114370.40	594.37	492336.00	184
	N2O	27761.30	53680.75	255.62	238336.70	184

AFR=Africa, ASIA= Asia, AUS= Australia, EUR=Europe, NAM= North America, SAM= South America, Count=Number of observation, std. Dev. =Standard deviation, min=Minimum value, max=Maximum value.

APPENDIX C

Average Energy Efficiency of Countries

Without environmental factors			With environmental factors		
DMU	**AM**	**GM**	**DMU**	**AM**	**GM**
Albania	0.163	0.162	Albania	0.490	0.380
Algeria	0.098	0.097	Algeria	0.110	0.100
Angola	0.143	0.134	Angola	0.190	0.170
Argentina	0.132	0.124	Argentina	0.100	0.090
Armenia	0.116	0.115	Armenia	0.500	0.350
Australia	0.220	0.218	Australia	0.130	0.130
Austria	0.352	0.350	Austria	0.220	0.220
Azerbaijan	0.084	0.072	Azerbaijan	0.130	0.110
Bahrain	0.226	0.217	Bahrain	0.230	0.190
Bangladesh	0.077	0.075	Bangladesh	0.270	0.180
Barbados	1.000	1.000	Barbados	1.000	1.000
Belarus	0.053	0.052	Belarus	0.080	0.070
Belgium	0.242	0.241	Belgium	0.150	0.150
Belize	0.762	0.753	Belize	1.000	1.000
Benin	0.072	0.072	Benin	0.280	0.210

Bolivia	0.098	0.096	Bolivia	0.190	0.160
Bosnia and Herzegovina	0.113	0.113	Bosnia and Herzegovina	0.200	0.180
Botswana	0.215	0.214	Botswana	0.350	0.320
Brazil	0.114	0.111	Brazil	0.080	0.080
Brunei Darussalam	0.824	0.799	Brunei Darussalam	0.770	0.730
Bulgaria	0.077	0.075	Bulgaria	0.110	0.100
Cambodia	0.069	0.069	Cambodia	0.210	0.170
Cameroon	0.097	0.097	Cameroon	0.190	0.160
Canada	0.151	0.151	Canada	0.090	0.090
Chile	0.159	0.158	Chile	0.130	0.130
China	0.033	0.031	China	0.030	0.030
Comoros	0.802	0.782	Comoros	1.000	1.000
Congo, Dem. Rep.	0.033	0.031	Congo, Dem. Rep.	0.120	0.100
Congo, Rep.	0.201	0.197	Congo, Rep.	0.650	0.500
Costa Rica	0.247	0.243	Costa Rica	0.330	0.290
Cote d'Ivoire	0.080	0.078	Cote d'Ivoire	0.170	0.140
Croatia	0.193	0.192	Croatia	0.170	0.170
Cuba	0.168	0.168	Cuba	0.190	0.180
Cyprus	0.956	0.948	Cyprus	1.000	1.000
Czech Republic	0.120	0.119	Czech Republic	0.090	0.090
Denmark	0.849	0.839	Denmark	0.850	0.830
Dominican Republic	0.181	0.180	Dominican Republic	0.230	0.210
Ecuador	0.152	0.151	Ecuador	0.170	0.160
Egypt	0.072	0.068	Egypt	0.080	0.070
El Salvador	0.146	0.141	El Salvador	0.380	0.270
Equatorial Guinea	0.221	0.185	Equatorial Guinea	1.000	1.000
Eritrea	0.144	0.136	Eritrea	0.700	0.480
Estonia	0.212	0.211	Estonia	0.170	0.170
Finland	0.221	0.218	Finland	0.150	0.150
France	0.217	0.209	France	0.140	0.140
Gabon	0.166	0.158	Gabon	0.290	0.260
Georgia	0.147	0.138	Georgia	0.260	0.220
Germany	0.179	0.153	Germany	0.140	0.130
Ghana	0.151	0.131	Ghana	0.190	0.160
Greece	0.206	0.175	Greece	0.180	0.180
Guatemala	0.120	0.120	Guatemala	0.190	0.170
Guinea-Bissau	0.341	0.341	Guinea-Bissau	0.530	0.480
Guyana	0.190	0.189	Guyana	0.220	0.220
Haiti	0.074	0.071	Haiti	0.400	0.250
Honduras	0.115	0.112	Honduras	0.260	0.210

Hungary	0.318	0.220	Hungary	0.120	0.120
Iceland	0.739	0.478	Iceland	1.000	1.000
India	0.038	0.035	India	0.060	0.050
Indonesia	0.049	0.048	Indonesia	0.060	0.050
Iran, Islamic Rep.	0.060	0.056	Iran, Islamic Rep.	0.050	0.040
Iraq	0.095	0.092	Iraq	0.110	0.100
Ireland	0.885	0.877	Ireland	0.790	0.750
Israel	0.318	0.310	Israel	0.210	0.200
Italy	0.270	0.268	Italy	0.170	0.170
Jamaica	0.160	0.158	Jamaica	0.330	0.270
Japan	0.217	0.210	Japan	0.130	0.130
Jordan	0.105	0.104	Jordan	0.260	0.210
Kazakhstan	0.053	0.051	Kazakhstan	0.060	0.060
Kenya	0.051	0.051	Kenya	0.120	0.100
Korea, Rep.	0.120	0.119	Korea, Rep.	0.080	0.070
Kuwait	0.479	0.367	Kuwait	0.430	0.270
Kyrgyz Republic	0.067	0.065	Kyrgyz Republic	0.320	0.220
Latvia	0.204	0.202	Latvia	0.210	0.200
Lebanon	0.189	0.187	Lebanon	0.230	0.220
Libya	0.153	0.148	Libya	0.110	0.100
Lithuania	0.323	0.227	Lithuania	0.160	0.150
Luxembourg	0.832	0.701	Luxembourg	1.000	1.000
Macedonia, FYR	0.130	0.128	Macedonia, FYR	0.290	0.260
Malaysia	0.276	0.155	Malaysia	0.080	0.080
Malta	0.791	0.739	Malta	0.930	0.920
Mauritius	0.269	0.249	Mauritius	0.790	0.670
Mexico	0.127	0.123	Mexico	0.090	0.090
Moldova	0.074	0.072	Moldova	0.420	0.270
Mongolia	0.084	0.081	Mongolia	0.200	0.170
Morocco	0.118	0.102	Morocco	0.170	0.150
Mozambique	0.074	0.054	Mozambique	0.140	0.110
Namibia	0.256	0.193	Namibia	0.840	0.710
Nepal	0.081	0.052	Nepal	0.140	0.100
Netherlands	0.337	0.315	Netherlands	0.230	0.190
New Zealand	0.213	0.200	New Zealand	0.160	0.160
Niger	0.072	0.070	Niger	0.750	0.490
Nigeria	0.046	0.041	Nigeria	0.070	0.050
Norway	0.556	0.537	Norway	0.550	0.470
Oman	0.213	0.173	Oman	0.180	0.130
Pakistan	0.050	0.049	Pakistan	0.080	0.070
Panama	0.266	0.264	Panama	0.340	0.310

Paraguay	0.127	0.122	Paraguay	0.250	0.200
Peru	0.188	0.178	Peru	0.170	0.160
Philippines	0.092	0.086	Philippines	0.110	0.090
Poland	0.114	0.113	Poland	0.080	0.080
Portugal	0.267	0.266	Portugal	0.170	0.170
Romania	0.102	0.097	Romania	0.100	0.090
Russian Federation	0.044	0.042	Russian Federation	0.030	0.030
Saudi Arabia	0.096	0.094	Saudi Arabia	0.060	0.060
Senegal	0.100	0.093	Senegal	0.360	0.240
Singapore	0.271	0.267	Singapore	0.190	0.180
Slovak Republic	0.147	0.146	Slovak Republic	0.120	0.120
Slovenia	0.258	0.257	Slovenia	0.180	0.180
South Africa	0.058	0.055	South Africa	0.060	0.050
Spain	0.236	0.234	Spain	0.150	0.150
Sri Lanka	0.115	0.110	Sri Lanka	0.190	0.150
Sudan	0.077	0.069	Sudan	0.160	0.120
Suriname	0.331	0.328	Suriname	0.820	0.740
Sweden	0.297	0.295	Sweden	0.200	0.190
Switzerland	0.967	0.957	Switzerland	1.000	1.000
Tajikistan	0.073	0.068	Tajikistan	0.570	0.350
Tanzania	0.037	0.035	Tanzania	0.110	0.080
Thailand	0.067	0.065	Thailand	0.060	0.050
Togo	0.055	0.051	Togo	0.440	0.270
Trinidad and Tobago	1.000	1.000	Trinidad and Tobago	1.000	1.000
Tunisia	0.186	0.144	Tunisia	0.250	0.190
Turkey	0.140	0.136	Turkey	0.110	0.100
Turkmenistan	0.040	0.040	Turkmenistan	0.070	0.070
Ukraine	0.027	0.026	Ukraine	0.040	0.040
United Arab Emirates	0.176	0.173	United Arab Emirates	0.110	0.110
United Kingdom	0.292	0.289	United Kingdom	0.180	0.180
United States	0.126	0.124	United States	0.080	0.070
Uruguay	0.365	0.311	Uruguay	0.370	0.290
Uzbekistan	0.021	0.020	Uzbekistan	0.050	0.040
Venezuela, RB	0.110	0.106	Venezuela, RB	0.090	0.080
Vietnam	0.050	0.045	Vietnam	0.080	0.060
Yemen, Rep.	0.161	0.111	Yemen, Rep.	0.310	0.200
Zambia	0.439	0.343	Zambia	1.000	1.000
Zimbabwe	0.052	0.050	Zimbabwe	0.170	0.140

GM=Geometric Mean, AM=Arithmetic Mean.

APPENDIX D

Commands for Analysis

R Commands

```
###Returns to scale test

t1=read.delim("clipboard")

x=matrix(rbind(t1$X1,t1$X2,t1$X3),nrow=3)##defining the set of inputs

y=matrix(rbind(t1$Y1,t1$Y2,t1$Y3,t1$Y4),nrow=4)##defining the set of outputs

t1

##RTS test Simar and WIlson (2002; 2011)

require(rDEA)


##Testing Ho that Technology is CRS

rts_g=rts.test(X=t(x),Y=t(y),W=NULL,model="output",H0="constant",bw="cv",B=1000,alpha=
0.05)

rts_g$w_hat## Simar and WIlson (2002) test statistic for Mean of Ratios

rts_g$pvalue## Simar and WIlson (2002) p-value for Mean of Ratios

rts_g$H0level## Simar and WIlson (2002) critical value for Mean of Ratios

rts_g$H0reject## Simar and WIlson (2002) critical value for Mean of Ratios

densityPlot(without~CONTINENT, data=utest, bw=bw.SJ, adjust=1.0,
kernel=dnorm,method="adaptive")

###SZAL TEST
```

```
d1=read.delim("clipboard") #export dat from excel

names(d1)

head(d1)

tail(d1)

datos1=utest[1:1955,]$score ##Define data for Group A

datos2=utest[1956:3910,]$score ##Define data for Group B


##NOW THE COMMANDS FOR THE SZAL PROCEDURE


#Datos ( The step I ):

h1<-dpik(datos1)

h2<-dpik(datos2)


# Commands to create density functions corresponding to the file data 1 :

datos12<-seq(length=150, from=min(datos1), by=((max(datos1)-min(datos1))/150))

samp2<-matrix(nrow=46,ncol=150)

for(j in 1:150){for(i in 1:46){samp2[i,j]<-(1/sqrt(2*pi))*exp(-.5*((datos12[j]-datos1[i])/h1)^2)}}

row.sums<-apply(samp2,2,sum)

row.sums.modif_datos1<-row.sums/(h1*length(datos1))

result_datos1<-cbind(datos12,row.sums.modif_datos1)
```

```
# Commands to create density functions corresponding to the file data2 :

datos22<-seq(length=150, from=min(datos2), by=((max(datos2)-min(datos2))/150))

samp2<-matrix(nrow=47,ncol=150)

for(j in 1:150){for(i in 1:47){samp2[i,j]<-(1/sqrt(2*pi))*exp(-.5*((datos22[j]-datos2[i])/h2)^2)}}

row.sums<-apply(samp2,2,sum)

row.sums.modif_datos2<-row.sums/(h2*length(datos2))

result_datos2<-cbind(datos22,row.sums.modif_datos2)


# Orders to carry out the graphs of density functions :

plot(datos12,row.sums.modif_datos1,type="l",xlim=c(min(datos1,datos2),max(datos1,datos2)),y
lim=c(min(row.sums.modif_datos1,row.sums.modif_datos2),max(row.sums.modif_datos1,row.s
ums.modif_datos2)),xlab="Value",ylab="Density",cex.main=1.8)

lines(datos22,row.sums.modif_datos2,type="l",lty=2,col=1,cex.main=1.8)


# And now come the corresponding orders to test for comparing data 1 vs. Li data2 :

#realizations<-realizations[!is.na(realizations)]

h1<-dpik(datos1)

h2<-dpik(datos2)

h<-min(h1,h2)

nA<-length(datos1)

nZ<-length(datos2)
```

```
lambda<-nA/nZ

samp1.no.diag<-matrix(nrow=nA,ncol=nA)
for(j in 1:nA){for(i in 1:nA){if (i>j | i<j) samp1.no.diag[i,j]<-dnorm((datos1[j]-datos1[i])/h)}}
samp1<-matrix(nrow=nA,ncol=nA)
for(j in 1:nA){for(i in 1:nA){samp1[i,j]<-dnorm((datos1[j]-datos1[i])/h)}}

primera.comp.I.no.diag<-sum(samp1.no.diag,na.rm=TRUE)/(h*nA*(nA-1))
primera.comp.I<-sum(samp1,na.rm=TRUE)/(h*nA^2)

#2ª componente:
samp2.no.diag<-matrix(nrow=nZ,ncol=nZ)
for(j in 1:nZ){for(i in 1:nZ){if (i>j | i<j) samp2.no.diag[i,j]<-dnorm((datos2[j]-datos2[i])/h)}}
samp2<-matrix(nrow=nZ,ncol=nZ)
for(j in 1:nZ){for(i in 1:nZ){samp2[i,j]<-dnorm((datos2[j]-datos2[i])/h)}}
segunda.comp.I.no.diag<-sum(samp2.no.diag,na.rm=TRUE)/(h*nZ*(nZ-1))
segunda.comp.I<-sum(samp2,na.rm=TRUE)/(h*nZ^2)

#3ª componente:
samp3.no.diag<-matrix(nrow=nA,ncol=nZ)
for(j in 1:nZ){for(i in 1:nA){if (i>j | i<j) samp3.no.diag[i,j]<-dnorm((datos2[j]-datos1[i])/h)}}
```

```
samp3<-matrix(nrow=nA,ncol=nZ)

for(j in 1:nZ){for(i in 1:nA){samp3[i,j]<-dnorm((datos2[j]-datos1[i])/h)}}

tercera.comp.I.no.diag<-sum(samp3.no.diag,na.rm=TRUE)/(h*nA*(nZ-1))

tercera.comp.I<-sum(samp3,na.rm=TRUE)/(h*nA*nZ)


#4ª componente:

samp4.no.diag<-matrix(nrow=nZ,ncol=nA)

for(j in 1:nA){for(i in 1:nZ){if (i>j | i<j) samp4.no.diag[i,j]<-dnorm((datos1[j]-datos2[i])/h)}}

samp4<-matrix(nrow=nZ,ncol=nA)

for(j in 1:nA){for(i in 1:nZ){samp4[i,j]<-dnorm((datos1[j]-datos2[i])/h)}}

cuarta.comp.I.no.diag<-sum(samp4.no.diag,na.rm=TRUE)/(h*(nA-1)*nZ)

cuarta.comp.I<-sum(samp4,na.rm=TRUE)/(h*nA*nZ)

# Here I put as scheduled Zelenyuk :

sigma.cuadrado<-
2*((1/(h*nA^2))*sum(samp1,na.rm=TRUE)+(lambda^2/(h*nZ^2))*sum(samp2,na.rm=TRUE)+
(lambda/(h*nA*nZ))*sum(samp3,na.rm=TRUE)+(lambda/(h*nA*nZ))*sum(samp4,na.rm=TRU
E))*1/(2*sqrt(pi))


#Esta es la componente I con los términos de la diagonal incluidos:

I.Li<-primera.comp.I+segunda.comp.I-tercera.comp.I-cuarta.comp.I


# This is the component I with the terms of the diagonal including :
```

```
I.Li.no.diag<-primera.comp.I.no.diag+segunda.comp.I.no.diag-tercera.comp.I.no.diag-
cuarta.comp.I.no.diag


# Of new , here I put as scheduled Zelenyuk :

T.formula<-nA*sqrt(h)*I.Li.no.diag/sqrt(sigma.cuadrado)

p.value<-1-pnorm(T.formula, mean = 0, sd = 1, lower.tail = TRUE, log.p = FALSE)


# This gives the value of the statistic used and the corresponding p- value . For interpretations ,
see the article by Simar and Russell:

print(T.formula)##The test statistic

print(p.value)##P-value


###MANN-WHITNEY U-TEST

wilcox.test(score~group,conf.int=TRUE,paired=FALSE,data=utest)


### T.test

ttest=read.delim("clipboard") #export dat from excel

t.test(score~group,conf.int=TRUE,paired=FALSE,data=d1)
```

Stata commands for the regression analysis

```
ivreg2 score gnipc inf popg interestrate exchangerate unemployment debt afr asia aus eur nam
sam (caplab = technology l.technology ), endogtest ( caplab) robust
```

outreg2 using Issah.doc, replace ctitle (RE Model
xtreg score caplab gnipc inf popg exchangerate interestrate unemployment debt afr asia aus eur nam sam, fe
estimate store fe
xtreg score caplab gnipc inf popg exchangerate interestrate unemployment debt afr asia aus eur nam sam, re
estimate store re
hausman fe re, sigmamore
reg score caplab gnipc inf popg exchangerate interestrate unemployment debt afr asia aus eur nam sam
xtset code year
hettest
xttest0
xtserial score caplab gnipc inf popg exchangerate interestrate unemployment debt afr asia aus eur nam sam
xtabond2 score l.score caplab gnipc inf popg exchangerate interestrate unemployment debt, gmm(l.score caplab, eq(diff) c) iv(gnipc inf popg exchangerate interestrate debt unemployment , eq(diff)) two small robust
xtabond2 score l.score caplab gnipc inf popg exchangerate interestrate unemployment debt, gmm(l.score caplab, lag (1 3) eq(diff) c) iv(gnipc inf popg exchangerate interestrate debt unemployment , eq(diff)) two small robust