UNIVERSITY OF GHANA

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IMPACT OF REGIONAL BLOCS ON THE ENERGY EFFICIENCY PATTERNS OF AFRICAN STATES: A MULTI- DIRECTIONAL EFFICIENCY ANALYSIS

BY

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THIS THESIS IS SUBMITTED TO THE UNIVERSITY OF GHANA, LEGON IN PARTIAL FULFILMENT OF THE REQUIREMENT FOR THE AWARD OF MPHIL IN FINANCE DEGREE.

APRIL, 2024

DECLARATION

I, Theophilus Abedu Quashie, hereby declare that the research presented in this work is entirely original and has not been previously submitted, either in part or in full, for academic recognition at this institution or any other. I affirm that I have conducted this research diligently and in accordance with the highest academic standards.

Throughout this study, I have meticulously cited all sources and references used, ensuring full transparency and integrity in acknowledging the contributions of others to this work. Any ideas, concepts, or data obtained from external sources have been appropriately attributed to their respective authors or creators.

I acknowledge that this research may have certain limitations, as is common in scholarly endeavors. However, I assume full responsibility for addressing and mitigating these limitations to the best of my ability. Furthermore, I am committed to upholding academic integrity and ethical conduct in all aspects of this research.

21st November, 2024

THEOPHILUS ABEDU QUASHIE DATE

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CERTIFICATION

I affirm that this thesis has been conducted in strict accordance with the established protocols and guidelines of the University of Ghana. Throughout the research process, I have adhered to the ethical standards and procedures set forth by the university, ensuring the integrity and credibility of this work.

.... 30/12/2025 ....

PROF. GODFRED ALUFAR BOKPIN DATE

(SUPERVISOR)

29th December, 2025

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DR. KWAKU OHENE-ASARE DATE

(CO-SUPERVISOR)

DEDICATION

This work is dedicated to the profound influences that have shaped my academic journey. It begins with heartfelt gratitude to the Holy Spirit, whose divine guidance and support have been ever-present throughout this endeavor.

I extend my deepest appreciation and love to my parents, Rev. Dr. and Mrs. Abedu Quashie, whose unwavering support and encouragement have been the cornerstone of my educational pursuit. Their sacrifices and belief in my abilities have been instrumental in shaping my path to success.

Lastly, I dedicate this work to Dr. Kwaku Ohene-Asare, my esteemed academic mentor. Dr. Ohene-Asare's belief in my potential and invaluable guidance have been a source of inspiration and motivation, driving me to strive for excellence in all endeavors.

In essence, this dedication is a sincere expression of gratitude to those who have contributed to my academic achievements and personal growth.

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With profound gratitude in my heart, I offer praise to the Almighty God, the eternal source of strength and blessings, whose wondrous guidance has illuminated every step of this research journey. To Him alone, I attribute all glory, honor, and praise.

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AREI	Africa Renewable Energy Initiative
AMU	Arab Maghreb Union
CEMA	Conference of Energy Ministers of Africa
CO2	Carbon Dioxide Emission
COMESA	Common Market for Eastern and Southern Africa
CRS	Constants Return to Scale
DEA	Data Envelopment Analysis
DMU	Decision Making Unit
EAC	East African Community
ECAS	Energy Consuming Africa States
ECCAS	Economic Community of Central African States
ECREEE	ECOWAS Centre for Renewable Energy and Energy Efficiency
ECOWAS	Economic Community of West African States
EEP	Energy Efficiency Policy
FEPC	Frontier Efficiency and Productivity Change Analysis
GDP	Gross Domestic Profit
IEA	International Energy Agency
IGAD	Intergovernmental Authority on Development
IRP	Ideal Reference Point

LP	Linear Programming
LPG	Liquefied Petroleum Gas
MEA	Multidirectional Efficiency Analysis
PIP	Potential Improvement Point
PV	Photo voltaic
REC	Regional economic communities
RBT	Resource Based Theory
SADC	Southern African Development Community
SDG	United Nation's Sustainable Development Goal
SFA	Stochastic Frontier Analysis
SSA	Sub-Saharan Africa
TPB	Theory of Planned Behaviour
VRS	Variable Returns to Scale

ABSRACT

This study investigates the impact of regional blocs on the energy efficiency patterns of African states using a multi-directional efficiency analysis approach. Adopting a quantitative research design, the study applies a novel Multi-Directional Efficiency Analysis (MEA) methodology alongside traditional Data Envelopment Analysis (DEA) to panel data from 32 African states over the period 2000 to 2019. The primary objectives are to assess environmental energy efficiency patterns, evaluate the energy efficiency status of African economies, explore energy consumption slacks and potential savings, and statistically compare variable-specific efficiencies across African regional blocs. The findings reveal significant variations in energy efficiency across countries and regional blocs, with some states exhibiting consistently higher efficiency scores than others. The MEA approach proves superior to DEA by effectively capturing both radial and non-radial slacks, thereby providing a more robust and nuanced assessment of energy efficiency. Furthermore, the results indicate that external factors such as population size, carbon dioxide emissions, level of technology, renewable energy use, and degree of government intervention significantly influence energy efficiency outcomes. The study also highlights the critical role of regional blocs in shaping energy efficiency dynamics, as disparities exist in their relative contributions to overall efficiency patterns. The findings have important policy implications, emphasizing the need for targeted regional and country-specific energy policies, increased investment in renewable energy and technological advancement, reduced carbon emissions, and enhanced collaboration and knowledge-sharing among African states and regional blocs to improve energy efficiency performance.

CHAPTER ONE

INTRODUCTION

1.1 Background of the study

Energy is the major source of growth and development in a country (Hossain et al., 2024; Shahbaz et al., 2020; Wang et al., 2022; Zheng et al., 2024). This includes solar, wind, hydro, geothermal, biomass which are all renewable sources and coal, petroleum, natural gas, nuclear which are non-renewable. (Fanchi, 2023; Ren et al., 2024; Zhang et al., 2018). Energy efficiency stands as a paramount concern for nations worldwide, spurred by environmental imperatives, economic aspirations, and geopolitical realities (Geopolitics, 2023; Hippel et al., 2011). The availability of energy is the basis for the development of human activities (Khan et al., 2021; Petrović et al., 2020). Concerns over energy security, economic stability and climate change has ignited a global debate on the future of energy source (Hassan et al., 2024; Hippel et al., 2011). Energy efficiency refers to the ability to produce a desired output or service while minimizing energy consumption (Greening et al., 2000; Patterson, 1996). Improving energy efficiency typically involves adopting technologies, practices, and strategies that reduce energy waste and enhance overall energy performance (Fazendeiro & Simões, 2021; Wang & Wang, 2020; Wang et al., 2013b; Wang et al., 2020; Wang et al., 2013; Wang et al., 2013). Furthermore, energy efficiency also entails decarbonization and reduction in other greenhouse gas (GHG) effect on the environment and health (Hamilton et al., 2016; Kermeli et al., 2014). In Africa, the quest for energy efficiency has escalated given the region's diverse energy landscape, characterized by abundant natural resources alongside persistent energy deficits and infrastructural challenges (Hafner et al., 2018; Irowarisima, 2021; Kessides, 2014). Against this backdrop, the emergence and operations of regional economic communities (RECs) in Africa has exerted a significant influence on the energy policies and pathways of member states, signifying the growing importance of regionalization in the realm of energy conservation (Ghorbani et al., 2024; Nalule, 2018). Some of these RECs include Economic Community of West African States (ECOWAS), the Southern African Development Community (SADC), and the East African Community (EAC), Common Market for Eastern and Southern Africa (COMESA), Arab Maghreb Union (AMU). These blocs have been established with the aim of fostering economic integration, enhancing trade relations, and collectively addressing shared challenges (Geda & Kebret, 2008; Mekonnen, 2019; Usman & Muhammad, 2024). Under these regionalizations, promotion of energy efficiency has risen to prominence, underscoring the pivotal role of energy in sustainable development and regional stability (Anser et al., 2024; Shah & Niles, 2016). It is crucial to assess not only the performance of countries in terms of efficiency, commonly known as efficiency status (that is, efficiency assessment of a decision-making unit, (DMU) as a whole), but also to examine how the inputs and outputs separately perform, providing a more comprehensive understanding of efficiency (Asmild et al., 2003a; Asmild & Matthews, 2012; Bogetoft & Hougaard, 2004; Kapelko & Lansink, 2017; Wang et al., 2013b). Generally, efficiency patterns examine how the parts of efficiency contributes to the whole. In other words, it disaggregates the aggregated efficiency in order to determine the contribution of each variable towards overall performance.

Another area worth considering is the influence of regionalisation on the energy efficiency of African states in an area that requires further inquiry (Alariqi et al., 2023; Awad, 2019; Facchini et al., 2017). Advocates of regionalisation assert that regional collaboration facilitates knowledge exchange, technology transfer, and economies of scale (Cooper, 2018; Pandey et al., 2022), while critics highlight institutional inefficiencies, divergent national interests, and unequal distribution of benefits among member states (Han et al., 2018; Siciliano et al., 2015; Yu & He, 2020). A nuanced understanding of how regionalisation impact energy efficiency patterns necessitates a comprehensive policy frameworks, institutional mechanisms, technological capacities, and socio-economic contexts (Bouzarovski & Herrero, 2017; Lal & Kumar, 2022). This allows the economies involved to achieve Sustainable Development Goal (SDG) 7.

Most energy efficiency studies use frontier methods such as stochastic frontier analysis (SFA) and data envelopment analysis (DEA) (Apergis et al., 2015; Bi et al., 2014; Bibi et al., 2021; Daraio et al., 2020; Jin & Kim, 2019; Koengkan et al., 2022; Li & Lin, 2015; Liddle & Sadorsky, 2021; Liu et al., 2023; Mahapatra & Irfan, 2023; Mardani et al., 2017; Ohene-Asare et al., 2020; Sarpong et al., 2022; Shui et al., 2015; Wang et al., 2013b; Yu et al., 2019) but just a few energy efficiency studies have utilized the non-radial, Multi-directional Efficiency Analysis (MEA) method (Wang et al., 2013b; Zhu et al., 2019). MEA is one of the non-radial models that aggregate non-radial slacks making it more discriminatory than the radial DEA. It selects targets so that variable improvements are proportional to the potential improvements identified by considering the improvement potential in each individual variable (Asmild et al., 2003a; Bogetoft & Hougaard, 1999b; Kapelko & Lansink, 2017) The main purpose of this study thus is to identify and evaluate the energy efficiency patterns of African states using the non-radial non-oriented MEA and to assess the impact of regional blocs on these efficiency patterns.

1.2 Problem Statement

Energy efficiency has become a critical policy priority for African states due to persistent energy supply constraints, rising energy costs, rapid growth in energy demand, and increasing environmental pressures associated with economic expansion and urbanisation (IEA, 2019;

World Bank, 2020; Adom, 2019). Many African economies continue to experience chronic electricity shortages, high production costs, and heavy dependence on fossil fuels, conditions that undermine industrial competitiveness and sustainable development (IEA, 2019; UNDP, 2021). In this context, improving energy efficiency is widely recognised as a cost-effective strategy for alleviating energy insecurity, reducing carbon emissions, and supporting long-term economic and environmental sustainability (Adom, 2019; Amowine et al., 2019). However, the effectiveness of energy efficiency policies in Africa depends largely on the availability of robust analytical tools capable of accurately measuring efficiency levels, identifying sources of inefficiency, and providing actionable improvement benchmarks across countries and regional blocs (Yu et al., 2019).

Despite the growing body of empirical research on energy efficiency, existing studies on African economies predominantly rely on traditional radial Data Envelopment Analysis (DEA) models (Zhou et al., 2008; Wu et al., 2015; Wang et al., 2015; Iftikhar et al., 2018). While radial DEA has been widely applied due to its computational simplicity, the literature demonstrates that it is limited in its ability to capture non-radial slacks, handle undesirable outputs such as carbon emissions, and reflect non-oriented production processes common in energy systems (Asmild & Matthews, 2012; Bi et al., 2014b; Yu et al., 2019). Consequently, radial DEA tends to overestimate efficiency scores and fails to provide detailed information on input reduction and output expansion potentials, thereby limiting its usefulness for policy formulation and targeted efficiency improvements. This methodological limitation creates a significant gap in the accurate assessment of energy efficiency patterns and improvement potentials among African states.

In response to these shortcomings, the Multi-Directional Efficiency Analysis (MEA) framework has been proposed in the efficiency literature as a more flexible and informative alternative to traditional DEA. MEA explicitly accounts for variable-specific improvement potentials by allowing inputs, desirable outputs, and undesirable outputs to adjust in different directions simultaneously (Bi et al., 2014; Wang et al., 2013b; Zhu et al., 2019). Empirical applications of MEA in sectors such as agriculture (Baležentis & De Witte, 2015), banking (Asmild & Matthews, 2012), and transportation (Bi et al., 2014b) demonstrate its superiority in capturing both radial and non-radial inefficiencies. However, despite its demonstrated advantages, the application of MEA in the African context remains extremely limited, particularly in cross-country energy efficiency studies (Amowine et al., 2019). This underutilisation represents a critical methodological gap, as it constrains the ability of researchers and policymakers to obtain nuanced insights into eco-efficiency performance across African economies.

Furthermore, although a few studies have begun to explore MEA within Africa, existing research has not applied this approach to comprehensively investigate the energy efficiency status, efficiency patterns, and improvement benchmarks of African states at the regional bloc level (Addo, 2022; Dowuona, 2014). The absence of MEA-based energy efficiency studies focusing on African regional blocs limits understanding of how regional integration frameworks influence efficiency outcomes and hinders the design of coordinated, region-specific energy policies. Addressing this gap is particularly important given the increasing emphasis on regional cooperation as a mechanism for improving energy access, reducing costs, and promoting sustainable energy transitions across the continent.

Against this backdrop, the present study seeks to address these methodological and empirical gaps by applying the Multi-Directional Efficiency Analysis framework to assess the energy efficiency patterns of African states and regional blocs. Specifically, the study aims to overcome the limitations of traditional radial DEA by capturing variable-specific inefficiencies and improvement potentials, to extend the application of MEA to the African energy context using cross-country panel data, and to provide a comparative analysis of energy efficiency patterns across African regional blocs. By doing so, the study contributes to the energy efficiency literature and provides policymakers with robust, evidence-based insights to support more effective and targeted energy efficiency strategies in Africa.

1.3 Research Objectives

The purpose of this study is to assess the status and patterns of environmental energy efficiencies of African States, determine their energy potential savings and explore the impact of regional blocs on such efficiencies. Specifically, the study seeks to:

1. To assess the patterns of environmental energy efficiency among African states using MEA.
2. To evaluate the overall environmental energy efficiency status of African states using MEA.
3. To determine energy consumption slacks and estimate potential energy savings of African states using MEA.
4. To compare variable-specific energy efficiency outcomes across African regional blocs.

1.4 Research Questions

For the research objectives to be realized, the following research questions must be addressed.

1. What are the environmental energy efficiency patterns of African states?
2. To what extent are the environmental energy efficiency of African states reasonable?

3. Which African state(s) show highest energy consumption slacks and energy saving potential?
4. To what extent do the environmental energy efficiency patterns of the African regional blocs differ?

1.5 Research Contribution

These are some of the main contributions that the study is outlining.

Firstly, on policy contribution, energy efficiency is achievable by means of setting up proper and precise energy policies to aid in the utilization and saving of energy because the performance of policies and programs that promote energy efficiency is very crucial. The study allows energy regulators to be able to prescribe policies that can help the African States within the regional blocs to efficiently utilize energy.

To academic contribution, the study will have a vast impact on contribution towards research. Generally, the number of worldwide studies applying the multi-directional efficiency analysis is few and this is recorded to be the first time the technique is been applied in Africa particularly in the energy sector. This is the first novel study to assess the environmental energy efficiency status and patterns of regional blocs of Energy Consuming African States (ECAS) and also the first study to investigate the energy consumption slacks and energy saving potential of ECAS. The impact of regional blocs on the efficiency patterns of energy consuming African states is an extended analysis which adds on to empirical studies.

Furthermore, the study has some managerial implications whereby it helps to identify the specific inputs and outputs that are being under-utilized as well as identify sources of their individual inefficiencies in order to find ways to improve them for the root.

Last but not least, the study aims at promoting the United Nation SDG 7 which aims to close the energy access gap and ensure access to affordable, reliable and sustainable energy for all by the year 2030 through efficient ways of using AFRICA, (EEHC, 2014) Energy Outlook. in African states.

1.6 Limitation of the Study

Limitations of the Study:

One of the primary limitations of this study may relate to the availability and quality of data. Energy efficiency data, especially on a regional or national scale in Africa, may be fragmented, outdated, or unreliable. This could potentially impact the robustness and generalizability of the findings.

The application of multi-directional efficiency analysis (MEA) in the African context may present methodological challenges. MEA requires detailed and comprehensive data on both inputs and outputs, which may not be readily available or standardized across different countries or regions in Africa. Moreover, the interpretation and implementation of MEA techniques could require specialized expertise, which may pose challenges in terms of replicability and comparability.

Africa is a vast and diverse continent with significant regional variations in terms of economic development, energy infrastructure, and policy frameworks. The study's findings may not fully capture the nuanced energy efficiency patterns within each region or country, potentially overlooking important regional differences that could influence the effectiveness of regional blocs.

Energy systems are complex and multifaceted, influenced by a myriad of factors including technological, socio-economic, and institutional dynamics. While the study aims to analyze the impact of regional blocs on energy efficiency patterns, it may not fully account for all the interacting variables and external factors that influence energy efficiency outcomes in African states.

The study may focus primarily on energy efficiency patterns and the influence of regional blocs, potentially overlooking other important aspects of energy sustainability such as renewable energy adoption, energy access, and energy affordability.

Addressing these limitations and acknowledging the uncertainties inherent in the study's findings will be crucial for interpreting and applying the results effectively, while also providing avenues for future research to further explore and refine our understanding of energy efficiency in Africa.

1.7 Thesis Structure

The study is made up of five chapters with subsections. The first chapter concentrates on the background of the study, problem statement, the research objectives and questions as well as the contributions and limitations of the study. Chapter two assesses relevant theoretical and empirical literature on efficiency studies in energy in order to provide evidence to buttress the research. The methodology of the research is highlighted in chapter three of the study as well as the research approach such as the research design and the sample size. Data presentation, results analysis, test execution, and graphical illustration are all covered in Chapter four and chapter five which is the final chapter concludes the study with a summary of the findings and policy recommendations based on the findings. Directions on additional research may be considered also.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter examines the theoretical and empirical literature on African states' energy efficiency patterns and the role of regional blocs in improving efficiency. The study looks at how to measure the efficiency of African states using MEA as well as the SZAL approach to discuss the role of regional blocs. The theoretical review lays the theoretical foundation for the study, whereas the empirical review examines existing research on energy efficiency patterns and status, as well as groupings' contributions to efficiency improvement.

2.2 Theoretical Review

2.2.1 Resource-Based Theory

Resource-Based Theory (RBT) provides a useful theoretical lens for explaining variations in performance across decision-making units that possess heterogeneous resource endowments. Originally developed within the strategic management literature, RBT posits that differences in performance arise from variations in the availability, quality, and utilisation of resources and capabilities, rather than from external conditions alone (Barney, 1991; Peteraf, 1993). Resources may be tangible or intangible and include physical capital, human capital, technological capabilities, institutional quality, and organisational competencies.

Although RBT was initially applied at the firm level, its core principles have been extended to higher levels of analysis, including industries, regions, and national economies. At the country level, RBT suggests that states endowed with superior resource combinations, such as advanced energy infrastructure, technological capability, skilled labour, effective institutions, and access to cleaner energy sources, are more likely to achieve higher levels of efficiency and productivity over time (Peteraf & Barney, 2003; Camisón & Villar-López, 2014). Conversely, countries with weaker resource bases or inefficient resource utilisation are likely to exhibit lower performance outcomes.

Within the context of energy efficiency, RBT provides a theoretical explanation for the observed heterogeneity in efficiency patterns across African states and regional blocs. Differences in energy resource endowments, capital stock, technological advancement, institutional capacity, and policy frameworks contribute to variations in how efficiently energy inputs are transformed into economic outputs while limiting environmental externalities. Empirical studies applying RBT-inspired reasoning in energy and productivity analysis have demonstrated that disparities in resource availability and management practices significantly influence efficiency outcomes (Ohene-Asare et al., 2018; Ohene-Asare & Turkson, 2019).

Importantly, RBT also supports the use of efficiency benchmarking approaches by emphasising that performance differences reflect varying capacities to exploit available resources effectively. In this study, African states are conceptualised as heterogeneous decision-making units whose relative energy efficiency depends on their ability to deploy energy, labour, capital, and technology efficiently. Regional blocs further shape these outcomes by facilitating resource sharing, policy coordination, and institutional learning among member states, thereby influencing collective and individual efficiency performance.

Overall, Resource-Based Theory underpins the study's analytical framework by justifying the expectation of cross-country and cross-regional variation in environmental energy efficiency. It provides a theoretical foundation for applying the Multi-Directional Efficiency Analysis (MEA) approach to identify efficiency patterns, benchmark best-performing states, and assess improvement potentials arising from differences in resource endowments and utilisation across African states and regional blocs.

2.1.2 Theory of planned behaviour

The Theory of Planned Behavior (TPB), originally proposed by Ajzen (1991) and subsequently refined by Ajzen (2020), extends the Theory of Reasoned Action by explaining how attitudes, subjective norms, and perceived behavioral control jointly shape intentions, which in turn influence observed behaviour. TPB has been widely applied in environmental and energy studies and is supported by substantial empirical evidence demonstrating its effectiveness in explaining pro-environmental and energy-related behaviours (Ajzen, 1985; Ajzen, 2020).

In the context of energy use and efficiency, TPB suggests that behavioural outcomes result from deliberate and rational decision-making processes informed by perceived costs and benefits, social expectations, and institutional constraints. Although TPB was initially developed to explain individual behaviour, its core constructs have been extended to organisational and policy contexts. At the national and regional levels, attitudes towards sustainability, prevailing policy norms, and perceived implementation capacity influence governments' willingness and ability to adopt energy-efficient technologies, enforce environmental regulations, and coordinate energy policies within regional blocs (Ajzen, 2020; Steg et al., 2014).

Complementing TPB, the Value-Belief-Norm (VBN) theory, introduced by Stern (2000), provides a normative explanation for environmentally oriented behaviour. VBN theory posits that pro-environmental actions are driven by underlying values; egoistic, altruistic, and biospheric, which shape beliefs about environmental consequences and responsibility for action. Empirical evidence indicates that individuals and institutions holding strong altruistic and biospheric values are more likely to support energy-saving measures and environmental policies (De-Groot & Steg, 2008; Poortinga et al., 2004).

According to VBN theory, values influence awareness of environmental problems and perceptions of responsibility, which in turn activate personal or collective norms that motivate pro-environmental action (Stern, 2000; Steg et al., 2005). Studies have shown that such normative commitments increase acceptance of energy efficiency policies and strengthen support for long-term sustainability initiatives (Steg et al., 2014).

Applied to African regional blocs, TPB and VBN together provide a useful framework for explaining differences in energy efficiency patterns across countries and regions. TPB helps explain how shared policy norms, institutional arrangements, and perceived administrative capacity within regional blocs, such as ECOWAS or SADC, influence the adoption and enforcement of energy efficiency policies. VBN theory, on the other hand, highlights how shared environmental values and collective commitments to sustainable development can motivate cooperation, policy harmonisation, and joint initiatives aimed at improving energy efficiency and reducing carbon emissions among member states.

The integration of TPB and VBN is therefore particularly relevant for interpreting cross-country and cross-regional variation in environmental energy efficiency. While TPB emphasises rational policy choice and institutional constraints, VBN underscores the role of values and moral responsibility in shaping environmental outcomes. Together, these theories complement the Resource-Based Theory by accounting for behavioural and normative influences on efficiency outcomes and support the application of the Multi-Directional Efficiency Analysis (MEA) framework to assess heterogeneous energy efficiency patterns across African states and regional blocs.

2.3 Empirical Review

2.3.1 Related Literature on Energy Efficiency

Energy efficiency is a central concept in energy economics and sustainability discourse, commonly defined as the ability to produce the same or higher levels of useful output with reduced energy input. Patterson (1996) defines energy efficiency as the use of less energy to deliver an equivalent level of goods or services, highlighting the importance of minimizing energy waste without compromising economic performance. Similarly, Song et al. (2013) emphasize energy efficiency as a deliberate effort to reduce energy losses while maximizing economic output, reinforcing the link between efficient energy use and productivity.

Beyond its technical definition, energy efficiency has become a critical policy objective due to growing concerns over energy scarcity, rising energy costs, and environmental degradation. In many developing regions, including Africa, increasing energy demand driven by population growth and economic expansion has intensified pressure on already constrained energy systems. As a result, improving energy efficiency is widely regarded as a cost-effective strategy for addressing energy shortages, enhancing energy security, and supporting sustainable economic growth (Bai et al., 2020; Fazendeiro & Simões, 2021).

The importance of energy efficiency is further underscored by its role in mitigating carbon dioxide (CO_2) emissions and addressing climate change. Empirical studies demonstrate that improvements in energy efficiency can significantly reduce emissions by lowering the amount of energy required to generate economic output (Bai et al., 2020; Paramati et al., 2022). This relationship is particularly relevant in African economies, where reliance on fossil fuels and inefficient energy technologies has contributed to rising emissions alongside economic growth (Adom et al., 2018).

Within the African context, and especially in West Africa, rapid urbanisation, industrialisation, and population growth have led to increasing energy consumption, often without corresponding improvements in energy efficiency. Several studies note that inefficiencies in energy use exacerbate supply constraints and increase production costs, thereby limiting economic competitiveness and social welfare (Adom, 2019; Sarpong et al., 2022). Consequently, African governments and regional institutions have increasingly prioritised energy efficiency as a strategic tool for reducing energy costs, improving environmental outcomes, and achieving sustainable development goals.

The existing literature identifies key drivers of energy efficiency, including energy consumption, capital stock, labour, technological progress, and economic output, typically measured by gross domestic product (GDP). These factors jointly influence the ability of countries to convert energy inputs into economic outputs while minimising environmental externalities. However, empirical findings suggest substantial variation in energy efficiency performance across countries and regions, reflecting differences in resource endowments, technological capability, and policy frameworks.

Overall, the literature highlights energy efficiency as a crucial mechanism for addressing the intertwined challenges of energy insecurity, environmental degradation, and sustainable development. Despite its growing importance, evidence from Africa remains fragmented, and cross-country and regional comparisons are limited. This underscores the need for comprehensive analytical approaches capable of capturing efficiency patterns, identifying sources of inefficiency, and informing targeted policy interventions within African states and regional blocs.

2.3.2 Empirical Applications of MEA

Multi-Directional Efficiency Analysis (MEA) is a non-parametric efficiency assessment technique developed to address limitations inherent in traditional radial Data Envelopment Analysis (DEA) models. Originally introduced by Bogetoft and Hougaard (1999) and further refined by Asmild et al. (2003) and Bogetoft and Leth Hougaard (2004), MEA allows for the simultaneous and variable-specific adjustment of inputs, desirable outputs, and undesirable outputs. This distinguishes MEA from conventional radial DEA approaches, which impose proportional changes across all variables and often fail to capture heterogeneous improvement potentials (Charnes et al., 1978; Banker et al., 1984).

The key strength of MEA lies in its ability to identify efficiency benchmarks based on the specific improvement potential associated with each input and output dimension. Rather than forcing decision-making units (DMUs) to adjust uniformly, MEA permits input reductions and output expansions to occur in different directions, making it particularly suitable for analysing systems characterised by multiple inputs, multiple outputs, and environmental externalities. As a result, MEA provides richer information on efficiency patterns, energy consumption slacks, and potential savings compared to traditional DEA models (Asmild et al., 2003; Asmild et al., 2019; Bi et al., 2014; Kapelko & Oude Lansink, 2017; Wang et al., 2013).

Despite its methodological advantages, the application of MEA remains relatively limited, partly due to its computational complexity and interpretational demands. Existing empirical studies applying MEA have largely focused on sectoral or firm-level analyses, including agriculture

(Baležentis & De Witte, 2015; Manevska-Tasevska et al., 2018), banking (Asmild & Matthews, 2012), higher education (Murillo, 2023), and environmental or emission efficiency in selected national or sub-national contexts (Jiang & Wang, 2024; Tian et al., 2023). These studies demonstrate MEA's ability to uncover efficiency heterogeneity, resource misallocation, and improvement potentials that are often obscured under radial DEA frameworks.

In the energy and environmental domain, MEA has been shown to be particularly effective in handling undesirable outputs such as carbon dioxide emissions and in identifying variable-specific inefficiencies related to energy use (Wang et al., 2013; Zhu et al., 2019). However, most existing applications remain concentrated in developed economies or emerging Asian contexts, with limited emphasis on Africa. More importantly, prior studies rarely examine energy efficiency patterns at the regional bloc level, despite the growing role of regional integration in shaping energy policy coordination, infrastructure development, and sustainability initiatives across African states.

Consequently, there is a notable gap in the empirical literature regarding the application of MEA to assess environmental energy efficiency patterns, energy consumption slacks, and energy savings potential across African countries, particularly within the framework of regional economic blocs. This study addresses this gap by applying MEA to African states and explicitly incorporating regional bloc comparisons, thereby extending the methodological and empirical scope of existing MEA-based efficiency studies and providing policy-relevant insights tailored to the African energy context.

2.3.3 Energy Efficiency Analysis Estimates

The estimation of energy efficiency has attracted considerable scholarly attention, resulting in the development and application of a wide range of analytical methods across both developed and developing economies. Countries such as the United States, Japan, Germany, the United Kingdom, China, and India, as well as several African nations, have employed diverse empirical approaches to evaluate energy efficiency performance and its determinants (Filippini & Hunt, 2015; Honma & Hu, 2014; Sueyoshi et al., 2017; Zhou et al., 2008).

Econometric techniques are commonly used to analyse energy efficiency by examining the relationship between energy consumption and its explanatory factors. Regression-based approaches, index decomposition analysis, and causality models have been applied to assess energy intensity, efficiency trends, and structural changes in energy use. For example, Filippini and Hunt (2015) employed regression models incorporating variables such as energy prices, income, climatic conditions, and capital stock to estimate energy efficiency at the sub-national level. Similarly, Otsuka and Goto (2018) used multiple regression analysis to examine the determinants of energy intensity and efficiency dynamics.

In addition to econometric methods, non-parametric techniques, particularly Data Envelopment Analysis (DEA), have become prominent tools for measuring energy efficiency. DEA, introduced by Charnes et al. (1978), evaluates the relative efficiency of decision-making units (DMUs) by comparing multiple inputs and outputs without requiring a predefined functional form. In the African context, several studies have employed DEA and related productivity indices to assess energy efficiency, including applications of single-factor productivity analysis, Malmquist productivity indices, and slack-based models (Boubaker, 2012; Olanrewaju et al., 2013; Sheng et al., 2017).

Studies in developed and emerging economies have further extended DEA-based analyses using Total Factor Productivity (TFP), Malmquist Productivity Index (MPI), Malmquist–Luenberger Index (MLI), and slack-based measures to account for undesirable outputs such as emissions (Chang & Hu, 2010; Gómez-Calvet et al., 2014; Honma & Hu, 2014; Sueyoshi et al., 2017). These studies highlight the versatility of DEA in capturing multi-input–multi-output production processes and incorporating environmental considerations into efficiency measurement.

Despite its widespread application, traditional DEA approaches are subject to important limitations, particularly their reliance on radial and orientation-specific assumptions. Such models often impose proportional input reductions or output expansions and may fail to adequately capture variable-specific inefficiencies, energy consumption slacks, and heterogeneous improvement potentials across DMUs. These limitations are especially relevant in the context of energy efficiency, where countries may face differing constraints across inputs, outputs, and environmental factors.

In response to these limitations, the Multi-Directional Efficiency Analysis (MEA) framework has been proposed as an alternative approach that allows inputs, desirable outputs, and undesirable outputs to adjust in different directions based on their specific improvement potentials (Bogetoft & Hougaard, 1999). MEA has been successfully applied in sectors such as healthcare, transportation, banking, and agriculture, where it has demonstrated superior capacity to identify efficiency patterns and improvement opportunities compared to traditional DEA models (Asmild & Matthews, 2012; Hailu & Veeman, 2001; Holvad et al., 2004).

However, the application of MEA to energy efficiency analysis, particularly within the African context, remains limited. Existing studies rarely examine energy efficiency patterns, energy consumption slacks, and potential energy savings at the national or regional bloc levels. This study addresses this gap by applying the MEA framework to assess environmental energy efficiency across African states, thereby providing a more nuanced understanding of efficiency levels, patterns, and improvement potentials and offering policy-relevant insights for sustainable energy development.

2.3.4 Energy Savings

Energy savings have become a central concern in the pursuit of sustainable economic development, particularly in energy-intensive economies. Growth in industrial energy consumption has been identified as a major driver of overall energy demand, with industrial expansion often accounting for a substantial share of increases in final energy use (Xiao et al., 2015). Consequently, improving energy efficiency and identifying energy saving potential have emerged as critical strategies for sustaining economic growth while reducing environmental pressure.

Historically, global economic development has been heavily dependent on non-renewable fossil fuels. This long-standing reliance has intensified concerns about resource depletion, environmental degradation, and energy security, thereby elevating the importance of energy saving as a means of decoupling economic growth from energy consumption (Li et al., 2017). Energy saving, in this context, refers to the reduction of unnecessary or avoidable energy consumption that does not contribute proportionately to the production of goods and services.

From an economic perspective, energy inefficiency often arises from information constraints, adjustment costs, and behavioural or institutional rigidities. While minimizing energy consumption to its technically optimal level may be theoretically desirable, achieving this outcome in practice involves costs related to information acquisition, technology adoption, and organisational change. As a result, economic agents, whether households, firms, or governments, may rationally tolerate higher-than-necessary energy consumption, thereby creating observable energy consumption slacks and unrealised energy saving potential (Jaffe & Stavins, 1994; Allcott & Greenstone, 2012; Gillingham & Palmer, 2014).

Behavioural theories further enrich the understanding of energy saving dynamics. Stern (2000) argues that energy-related decisions are influenced not only by rational cost-benefit considerations but also by underlying values and moral norms. The Value-Belief-Norm (VBN) theory suggests that individuals and institutions are more likely to support and adopt energy saving measures when they hold strong altruistic and biospheric values. Empirical evidence indicates that concern for others and the environment enhances public acceptance of energy conservation policies and initiatives (De-Groot & Steg, 2008; Poortinga et al., 2004).

Moreover, when actors perceive themselves as responsible for environmental problems, this awareness activates moral obligations that increase support for energy efficiency policies and behavioural change (Steg et al., 2005). At the policy level, such normative orientations can translate into stronger regulatory frameworks, greater investment in energy-efficient technologies, and coordinated efforts to reduce energy waste.

Despite the recognised importance of energy savings, many empirical studies focus primarily on aggregate efficiency scores without explicitly quantifying energy consumption slacks or potential energy savings. This limits the usefulness of such analyses for policy formulation, particularly in developing regions where energy supply constraints and rising demand coexist. Identifying the magnitude and sources of energy saving potential is therefore essential for designing targeted interventions that address specific inefficiencies.

In this regard, analytical approaches capable of decomposing inefficiencies and identifying variable-specific energy consumption slacks are particularly valuable. By quantifying energy saving potential alongside efficiency levels, such approaches provide actionable insights for policymakers seeking to reduce energy waste, enhance sustainability, and improve overall energy system performance.

2.3.5 Empirical Study on Energy Efficiency in Africa

Africa consumes significantly less energy per capita than the global average; however, energy efficiency across the continent remains relatively low, with important implications for sustainable development and energy security (Ohene-Asare & Turkson, 2019). Improving energy efficiency has been identified as a key strategy for enhancing energy security, strengthening industrial competitiveness, and reducing environmental externalities such as carbon dioxide emissions (Wang et al., 2017). In response to mounting evidence of anthropogenic climate change, countries worldwide; including those in Africa, have increasingly adopted energy efficiency and renewable energy policies as part of broader sustainability agendas (Baye et al., 2021; Wang et al., 2017).

Despite these global efforts, progress in African countries has been comparatively limited. While developed economies have achieved notable success in decoupling energy consumption from economic growth and environmental pollution, similar outcomes have not been widely observed across developing regions, particularly in Africa (Adom, 2019). Since 2010, many African countries have undertaken reforms to expand electricity generation capacity and improve access to modern energy services as part of poverty reduction and inclusive growth strategies. Nonetheless, access to electricity remains low, with only about 48% of the African population having access in 2019, compared to 87% in developing economies globally (Afful-Dadzie et al., 2020; Newell et al., 2020).

Although Africa accounts for approximately 17% of the global population, its share of global primary energy consumption and electricity demand remains disproportionately small (Ohene-Asare et al., 2020; Yang & Khan, 2022). Electricity consumption is also unevenly distributed across the continent, with Northern and Southern Africa accounting for the majority of usage, while Sub-Saharan Africa (excluding South Africa) contributes a relatively small share of total electricity consumption (Alemzero & Huaping, 2021). Paradoxically, Sub-Saharan Africa remains one of the most energy-intensive regions globally, requiring relatively high levels of energy input to generate a unit of economic output. This outcome has been attributed to both technical and institutional challenges, including high transmission and distribution losses, inefficient pricing structures, limited cost recovery, and widespread system losses.

Empirical research on energy efficiency in Africa remains limited and fragmented. Existing studies have primarily employed traditional efficiency measurement techniques such as Data Envelopment Analysis (DEA), stochastic frontier analysis, and productivity indices. For example, Adom (2019) analysed energy efficiency performance in 22 African economies, while Ramanathan (2005) examined energy use and emissions in the Middle East and North Africa region. Other studies, including Amowine et al. (2019), Boubaker (2012), Jebali et al. (2017), Olanrewaju et al. (2013), Ouedraogo (2017), Sheng et al. (2017), and Tongsopit et al. (2016), applied DEA and related methods to assess energy efficiency in selected African countries and sectors.

However, a critical review of the African energy efficiency literature reveals three important limitations. First, most studies rely on radial or orientation-specific DEA models, which impose proportional adjustments across inputs and outputs and often fail to capture variable-specific inefficiencies. Second, existing studies rarely quantify energy consumption slacks or estimate potential energy savings, limiting their usefulness for targeted policy design. Third, and most importantly, there is a notable absence of studies applying Multi-Directional Efficiency Analysis (MEA) to assess environmental energy efficiency patterns across African states, particularly within the context of regional economic blocs.

This study addresses these gaps by applying the MEA framework to evaluate environmental energy efficiency across African states and regional blocs. By explicitly capturing efficiency patterns, energy consumption slacks, and potential energy savings, the study provides a more nuanced and policy-relevant assessment of energy efficiency performance in Africa and contributes to the advancement of empirical research in this area.

2.3.6 Related Literature on Second Stage Regression Analysis

Second-stage regression analysis is commonly employed in efficiency studies to examine the influence of external or environmental factors on efficiency scores obtained from first-stage efficiency models. In the context of Data Envelopment Analysis (DEA), this approach is particularly important because estimated efficiency scores are not directly observable and are subject to statistical dependence arising from the deterministic nature of the DEA methodology (Simar & Wilson, 2007, 2011).

Simar and Wilson (2007) argue that conventional second-stage regression techniques may produce biased and inconsistent estimates when applied directly to DEA efficiency scores, due to serial correlation and the bounded nature of the efficiency estimates. To address these concerns, they propose bootstrap-based truncated regression models that provide statistically valid inference. Subsequent studies have reinforced the importance of accounting for sampling variation, measurement error, and the influence of exogenous environmental variables when conducting second-stage efficiency analysis (Daraio & Simar, 2007).

Ignoring environmental or contextual factors can lead to biased assessments of performance, as efficiency outcomes may be influenced by variables beyond the control of decision-making units (Dyson et al., 2001). As a result, several scholars advocate the use of second-stage regression analysis to evaluate the effects of factors such as population size, technological development, energy structure, institutional quality, and policy environments on efficiency performance (Fried et al., 2002; Wang et al., 2019). Sensitivity analysis is also recommended to assess the robustness of efficiency estimates and to ensure the reliability of policy-relevant conclusions.

In the energy efficiency literature, a variety of second-stage regression techniques have been applied, including Tobit, ordinary least squares (OLS), and panel regression models, to examine the determinants of efficiency and productivity change. Empirical studies by Amowine et al. (2019), Apergis et al. (2015), Borozan (2018), Honma and Hu (2008), Lv et al. (2015), Ren et al. (2020), Zeng et al. (2020), and Zhang et al. (2011) demonstrate the widespread use of such models to identify key drivers of energy efficiency across countries and sectors.

Despite the growing body of literature on second-stage analysis in DEA-based energy efficiency studies, the application of second-stage regression analysis to Multi-Directional Efficiency Analysis (MEA) remains limited. Most existing studies applying MEA focus primarily on first-stage efficiency measurement, with little attention paid to systematically analysing the determinants of MEA-based efficiency scores. Consequently, there is a methodological gap regarding the integration of MEA with robust second-stage regression techniques, particularly in the context of energy efficiency analysis in Africa.

This study addresses this gap by extending the MEA framework to include second-stage regression analysis, enabling the examination of how external factors influence environmental energy efficiency patterns across African states and regional blocs. By combining MEA with second-stage regression analysis, the study provides a more comprehensive understanding of both efficiency performance and its underlying drivers, thereby enhancing the policy relevance and empirical contribution of the research.

2.3.7 Related Literature on African Regional Bloc

Africa accounts for a disproportionately large share of the global population without access to modern energy services, hosting nearly half of the world's population lacking access to electricity and a quarter of those dependent on traditional biomass for cooking, despite representing approximately 18% of the global population (Agency & Birol, 2013; Van-der-Hoeven, 2013). Although per capita energy consumption in Africa remains below the global average, energy efficiency performance across the continent is relatively poor. This inefficiency is further compounded by persistent structural challenges such as unreliable electricity supply, frequent power outages, and power rationing (Wolde-Rufael, 2005, 2009).

Energy demand in Africa is expanding at nearly twice the global average, driven by population growth, urbanisation, industrial expansion, and declining renewable energy technology costs. This trend has accelerated the deployment of renewable energy technologies, particularly solar photovoltaics, while simultaneously increasing demand for oil and gas products due to transport sector expansion and the adoption of liquefied petroleum gas (LPG) for clean cooking (Simons, 2019). Despite these developments, Africa's primary energy consumption remains dominated by traditional biomass, which accounts for approximately 77% of total primary energy use, highlighting persistent inefficiencies in energy use and conversion (Simons, 2019).

In response to these challenges, African regional economic blocs have emerged as key institutional actors in coordinating energy policy, infrastructure development, and sustainability initiatives. The African Union (AU), through its Energy Development Strategies and Initiatives, has prioritised energy access, environmental sustainability, and energy efficiency. Complementary regional initiatives include the Programme for Infrastructure Development in Africa (PIDA), the Africa Renewable Energy Initiative (AREI), and the Africa Bioenergy Policy Framework (Pielli et al., 2016). Similarly, sub-regional blocs such as ECOWAS have embedded energy efficiency into their legal and policy frameworks, notably through Article 43 of the ECOWAS Energy Protocol and the establishment of the ECOWAS Centre for Renewable Energy and Energy Efficiency (ECREEE).

Beyond ECOWAS, other African regional blocs, including AMU, COMESA, CEN-SAD, EAC, ECCAS, IGAD, and SADC; play critical roles in shaping regional energy markets and policy coordination. These blocs influence investment priorities, regulatory harmonisation, and technology diffusion, thereby creating shared institutional and infrastructural environments that may lead to distinct energy efficiency patterns across regions (Auth et al., 2014). Consequently, regional blocs represent meaningful analytical units for examining energy efficiency performance, environmental energy efficiency patterns, and cross-country heterogeneity within the African energy landscape.

Despite the central role of regional blocs in energy governance, empirical research assessing energy efficiency in Africa has largely adopted country-specific approaches. Existing studies predominantly focus on the relationship between energy consumption and economic growth or emissions rather than directly evaluating energy efficiency performance across countries within regional blocs (Akinlo, 2008; Ohene-Asare & Turkson, 2019; Ouedraogo, 2013). Where multi-country analyses exist, they are often limited to subsets of ECOWAS countries, thereby restricting the ability to draw continent-wide or bloc-level comparisons (Wolde-Rufael, 2009).

More importantly, the existing literature rarely examines energy consumption slacks, unrealised energy saving potential, or the "reasonableness" of observed energy efficiency patterns across African regional blocs. This limitation constrains policy relevance, as identifying slack-adjusted inefficiencies and regional disparities is crucial for designing targeted and cost-effective energy efficiency interventions. Furthermore, most studies rely on conventional radial DEA or index-based methods, which obscure variable-specific inefficiencies and fail to capture multidirectional improvement potentials.

Against this backdrop, there is a clear gap in the literature regarding the systematic assessment of environmental energy efficiency across African regional blocs using advanced non-radial efficiency techniques. This study addresses this gap by applying Multi-Directional Efficiency Analysis (MEA) to evaluate energy efficiency levels, energy consumption slacks, and energy saving potential across African states and regional economic blocs. By doing so, the study enables robust inter-bloc benchmarking and provides policy-relevant insights aligned with the strategic objectives of African regional institutions.

2.4 conclusion

In conclusion, the literature review examined both theoretical and empirical literature related to energy efficiency patterns in African states and the role of regional blocs in improving efficiency. The theoretical review delved into Resource-Based Theory (RBT) and the Theory of Planned Behavior (TPB) to provide a theoretical foundation for understanding how firms and individuals can enhance efficiency.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

The statistical methods used to achieve the goals of the study are described in depth in this chapter. It emphasizes the tools and techniques used to estimate efficiency scores and test for the group differences in distribution of efficiency scores. The study design, the data source, and the techniques and instruments for data analysis are all included in this chapter.

3.2 Research Design

The research design provides a structured plan for collecting, analyzing, and interpreting data in a way that addresses the research objectives and ensures the study's findings are valid and reliable. It outlines the procedures and techniques adopted to answer the research questions and achieve the purpose of the study.

This study adopts a non-experimental quantitative research design, which is appropriate given that it relies on secondary data and does not involve manipulation of variables. The non-experimental approach allows the researcher to observe and analyze naturally occurring phenomena, making it suitable for examining energy efficiency patterns across African states over the period 2000–2019.

The study follows a post-positivist philosophical stance, underpinned by determinism. This paradigm assumes that relationships exist among variables and can be empirically observed, measured, and analyzed to explain and forecast outcomes (Creswell, 2014; Phillips et al., 2000). By adopting this stance, the study seeks to uncover causal relationships between energy efficiency and its determinants while maintaining an objective and systematic approach to data analysis.

Numerical data are analyzed using statistical and efficiency measurement methods, allowing for a robust assessment of energy efficiency patterns, identification of inefficiencies, and evaluation of energy saving potentials. This design also enables the study to examine differences across regional blocs and the effects of external determinants on energy efficiency. By clearly specifying the study design at the outset, the research ensures that subsequent methodological steps, including DEA, MEA, returns-to-scale testing, and panel regression analysis, are logically framed and coherent with the research objectives.

3.3 Sampling and sources of Data

Data from Penn World Tables (PWT 10.0) and US Energy Information Administration (EIA) will be used in the study. Data collected is based on the inputs and outputs used in the study that is, capital services, labour, energy used and Real GDP, CO_2 emissions, methane emissions respectively as well as various groupings of African states. An unbalanced cross-country of 32

African states over the period of 2000 to 2019 is used for this study due to time constraint and unavailability of some data.

3.4 Frontier efficiency analysis

Frontier Efficiency and Productivity Change Analysis (FEPC) is a robust non-parametric method employed to gauge the relative efficiency and productivity shifts among decision-making units (DMUs) (Cook et al., 2013; Kumbhakar et al., 2013; Simar & Zelenyuk, 2011). This methodology amalgamates principles from both Data Envelopment Analysis (DEA) and Malmquist Productivity Index (MPI), offering a comprehensive assessment framework.

Initially, FEPC utilizes DEA to delineate the efficient frontier, representing the set of DMUs that optimally utilize inputs to produce desired outputs. DMUs positioned on this frontier are deemed efficient, while those falling below are labeled as inefficient (Cook et al., 2014). Subsequently, FEPC employs the MPI to quantify productivity changes over time. The MPI computes alterations in the distance between the efficient frontiers of two time periods and the distance between each DMU and the efficient frontier of the initial period (Wang & Lan, 2011). This facilitates the measurement of productivity shifts attributed to technological advancements and efficiency enhancements (Winston, 1957).

The literature on measuring productive efficiency has gained momentum over the past three decades, inspired by Farrell's seminal work Farrell (1957), which conceptualized efficiency deviations from an idealized frontier isoquant. Fried et al. (1993) and Coelli et al. (1998) offer valuable insights into this domain, emphasizing the empirical identification of efficient benchmarks. Efficiency is typically evaluated by benchmarking against "best practice" frontiers established by the industry's most efficient entities, while productivity gauges the efficiency scores of these frontiers against each other (Shephard, 1953)

Efficiency and productivity measurement can be approached through parametric and non-parametric methods. Parametric tests, such as Stochastic Frontier Analysis (SFA), assume specific data distributions, like the normal distribution, and employ techniques like t-tests and analysis of variance to compare groups or study variable relationships (Greene, 2005; Greene, 2008). Conversely, non-parametric methods, exemplified by DEA, eschew distributional assumptions and utilize linear programming to estimate frontiers (Cooper et al., 2004; Färe et al., 2008; Thanassoulis et al., 2008). These methods are favored for analyzing skewed data and situations where data transformation may not render it suitable for parametric analyses.

In essence, FEPC serves as a powerful analytical tool for assessing efficiency and productivity shifts, offering flexibility and robustness across various empirical contexts.

3.5 Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) stands as a pivotal nonparametric linear programming technique utilized to evaluate the relative efficiency and productivity changes among homogeneous decision-making units (DMUs) that leverage multiple inputs to yield multiple outputs, while upholding the principles of strong free disposability and convexity (Charles et al., 2020; Charnes et al., 1978a; Lampe & Hilgers, 2015; Liu et al., 2016; Liu et al., 2013a, 2013b). Originating from the work of Charnes et al. (1978c) under constant returns to scale (CRS) and subsequently extended by Banker et al. (1984) under variable returns to scale (VRS), DEA is instrumental in assessing the relative efficiency of observed DMUs by establishing a convex linear envelopment technology frontier, with outliers serving as boundary units. The distance between a unit and this frontier is then employed to gauge the relative efficiencies of all DMUs Daraio et al. (2020); (Fethi & Pasiouras, 2010; Liu et al., 2013a), with units on the boundary of the production possibility set deemed efficient and those within labeled as inefficient.

The widespread application of DEA spans various domains, including energy (Ohene-Asare et al., 2020; Ohene-Asare & Turkson, 2019; Zhou et al., 2018; Zhou et al., 2012), agriculture (Albertini et al., 2021; Andre et al., 2010; Emrouznejad & Yang, 2018; Liu et al., 2013b; Nastis et al., 2019; Peykani et al., 2020), insurance (Kaffash et al., 2020; Ohene-Asare et al., 2019; Wise, 2017), banking (Ahmad et al., 2020; Ahmed & Bhatti, 2020; Alhassan & Ohene-Asare, 2016; Bhatia et al., 2018; Hassan & Aliyu, 2018; Hassan et al., 2019; Liu et al., 2016; Ohene-Asare & Asmild, 2012) and health (Emrouznejad & Yang, 2018; Liu et al., 2013b). The essence of DEA lies in benchmarking each DMU's performance against that of others in the sample, constructing a frontier of best practice based on the most efficient DMUs. Subsequently, the efficiency score of each DMU is determined as the ratio of its weighted outputs to its weighted inputs, optimizing efficiency while holding other DMUs' scores constant (Dyson et al., 2001; Lampe & Hilgers, 2015; Liu et al., 2013b).

DEA presents notable advantages over traditional econometric methods. Firstly, it circumvents the need for assumptions regarding the functional form of the production function or the distribution of error terms (Emrouznejad & Yang, 2018; Liu et al., 2013b). Secondly, DEA accommodates multiple inputs and outputs simultaneously, facilitating comparisons across organizations that produce diverse goods and services. Lastly, DEA furnishes a measure of relative efficiency, facilitating the identification of best practices and benchmarking against peers

(Kaffash et al., 2020; Lampe & Hilgers, 2015; Pastor & Aparicio, 2015; Wu et al., 2006; Zhou et al., 2008).

However, DEA does possess limitations. Firstly, it presupposes that all DMUs operate under identical technology and production constraints, which may not hold true in practice. Secondly, DEA assumes fixed and exogenous weights, potentially misrepresenting a DMU's actual production process. Finally, DEA does not offer insights into the sources of inefficiency or strategies for performance improvement (Asmild et al., 2003b; Bogetoft & Hougaard, 1999a; Kapelko & Lansink, 2018; Sueyoshi & Wang, 2014; tone, 2010; Tziogkidis et al., 2020).

3.5.1 Assumptions of DEA

Free disposability (monotonicity) - DMUs can use more inputs & produce less outputs than observed (i.e., operate inefficiently). If $(x', y') \in \Psi$, then $(x, y) = (x' + \alpha, y' - \beta) \in \Psi, \forall \alpha, \beta \geq 0$

It is a property of preferences that states that adding more of a good to a set of available alternatives can never make that set less attractive.

Convexity or VRS - weighted averages (line segments between observations) are feasible or convex combinations of feasible production plans is feasible as well - (FDH relaxes this axiom). If $(x', y') \in \Psi$, and If $(x'', y'') \in \Psi$, then $(x, y) = c\,(x', y') + (1 - c)\,(x'', y'') \in \Psi, \forall c \geq 0$.

No-free lunch axiom: No output is possible unless some input is used.

Returns to scale or homogeneity conditions i.e., some rescaling is possible. There is vrs & crs ("ray unboundness" in Banker et al. 1984) or full proportionality between all inputs & outputs (Barros et al, 2010).

CRS implies that If (x', y') ∈ Ψ, then (x, y) = d (x', y') ∈ Ψ, ∀d ≥ 0. CRS means a proportionate increase in inputs results in the same proportionate increase in outputs.

3.5.2 Formalising the basic DEA model

To formalize the basic DEA CCR model, we assume that in a production technology set T, there are N decision-making units (DMUs) which produce s non-negative outputs y_r using m non-negative inputs x_i, where a specific DMU j uses x_{ij} input i to produce y_{rj} quantities of output r. This is also known as the production possibility set (PPS), which forms the basis for efficiency analysis (Farrell, 1957). The technology set T can then be defined as:

$$T = \{(x, y) \in \Re^{m+s} / x \text{ can produce } y\}$$

They serve as the foundation for developing the efficient frontier. Using the technology set is acceptable because, given specified input amounts, a firm is capable of producing particular levels of outputs that belong to the technology set (Coelli et al., 2005). After the input and output vectors for a group of DMUs have been established, the PPS within which the DMUs operate is defined.

Typically, a DEA model may be classified as either input or output oriented (Lovell & Pastor, 1999). The input-oriented framework, based on the input requirement set and its efficient boundaries, seeks to reduce input quantities as much as feasible while maintaining at least the current output levels.

Input Orientation

$$\theta^t\left(y^t, x^t\right) = \min_{\lambda,\theta} \theta$$

$$s.t.:\begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij}^{t} \leq \theta x_{i0}^{t}; & i = 1,2,\ldots,m \\ \sum_{j=1}^{n} \lambda_j y_{rj}^{t} \geq y_{r0}^{t}; & r = 1,2,\ldots,s \\ \sum_{j=1}^{n} \lambda_j = 1 \text{ (VRS)} & \\ \lambda_j \geq 0, \quad x_i \geq 0; & j = 1,2,\ldots,n \\ t = 1, 2, \ldots, T & \end{cases}$$

$$\theta^{t+1}\left(y^{t+1}, x^{t+1}\right) = \min_{\lambda,\theta} \theta$$

$$s.t.:\begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij}^{t+1} \leq \theta x_{i0}^{t+1}; \quad i = 1,2,\ldots,m \\ \sum_{j=1}^{n} \lambda_j y_{rj}^{t+1} \geq y_{r0}^{t+1}; \ r = 1,2,\ldots,s \\ \sum_{j=1}^{n} \lambda_j = 1 \text{ (VRS)} \\ \lambda_j \geq 0, \quad x_i \geq 0; \quad j = 1,2,\ldots,n \\ t = 1, 2, \ldots, T \end{cases}$$

$$\theta^{t+1}\left(y^{t}, x^{t}\right) = \min_{\lambda,\theta} \theta$$

$$s.t.:\begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij}^{t+1} \leq \theta x_{i0}^{t}; & i = 1,2,\ldots,m \\ \sum_{j=1}^{n} \lambda_j y_{rj}^{t+1} \geq y_{r0}^{t}; & r = 1,2,\ldots,s \\ \sum_{j=1}^{n} \lambda_j = 1 \text{ (VRS)} & \\ \lambda_j \geq 0, \quad x_i \geq 0; & j = 1,2,\ldots,n \\ t = 1, 2, \ldots, T & \end{cases}$$

Output Orientation

$$\theta^{t}\left(y^{t},x^{t}\right) = \max_{\lambda,\theta} \theta$$

$$s.t.:\begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij}^{t} \leq x_{i0}^{t}; & i = 1,2,\dots,m \\ \sum_{j=1}^{n} \lambda_j y_{rj}^{t} \geq \emptyset y_{r0}^{t}; & r = 1,2,\dots,s \\ \sum_{j=1}^{n} \lambda_j = 1 \text{ (VRS)} & \\ \lambda_j \geq 0, \quad x_i \geq 0; & j = 1,2,\dots,n \\ t = 1,2,\dots,T & \end{cases}$$

$$\theta^{t+1}\left(y^{t+1},x^{t+1}\right) = \max_{\lambda,\theta} \theta$$

$$s.t.:\begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij}^{t+1} \leq x_{i0}^{t+1}; & i = 1,2,\dots,m \\ \sum_{j=1}^{n} \lambda_j y_{rj}^{t+1} \geq \emptyset y_{r0}^{t+1}; & r = 1,2,\dots,s \\ \sum_{j=1}^{n} \lambda_j = 1 \text{ (VRS)} & \\ \lambda_j \geq 0, \quad x_i \geq 0; & j = 1,2,\dots,n \\ t = 1,2,\dots,T & \end{cases}$$

$$\theta^{t+1}\left(y^{t},x^{t}\right) = \max_{\lambda,\theta} \theta$$

$$s.t.:\begin{cases} \sum_{j=1}^{n} \lambda_j \, x_{ij}^{t+1} \leq x_{io}^{t}; \quad i = 1,2,\ldots,m \\ \sum_{j=1}^{n} \lambda_j \, y_{rj}^{t+1} \geq \emptyset y_{ro}^{t}; \; r = 1,2,\ldots,s \\ \sum_{j=1}^{n} \lambda_j = 1 \text{ (VRS)} \\ \lambda_j \geq 0, \;\; x_i \geq 0; \quad j = 1,2,\ldots,n \\ t = 1, 2, \ldots, T \end{cases}$$

3.5.3 Illustrative example

Table 1: Hypothetical data for numerical example

DMUs	x1	y1
A	2.5	2.5
B	4	2
C	5	10
D	7.5	11.5
E	9	11.5
F	7	5
G	2.5	1
H	5	4
I	7.5	7

Output orientation

$$\Phi^{*}_{rF} = \max_{\lambda_{A-I},\phi} \phi_{rF}$$

s.t.

$2.5\lambda_A + 4\lambda_B + 5\lambda_C + 7.5\lambda_D + 9\lambda_E + 7\lambda_F + 2.5\lambda_G + 5\lambda_H + 7.5\lambda_I \leq 7$ (input x constraint)

$2.5\lambda_A + 2\lambda_B + 10\lambda_C + 11.5\lambda_D + 11.5\lambda_E + 5\lambda_F + 1\lambda_G + 4\lambda_H + 7\lambda_I \geq 5\phi$ (output y constraint)

$\lambda_A + \lambda_B + \lambda_C + \lambda_D + \lambda_E + \lambda_F + \lambda_G + \lambda_H + \lambda_I = 1$ (convexity constraint)

$\phi, \lambda_A, \lambda_B, \lambda_C, \lambda_D, \lambda_E, \lambda_F, \lambda_G, \lambda_H, \lambda_I \geq 0$ (non-negativity constraint)

Input Orientation

$$\theta^{*t}\left(y^t, x^t\right) = \min_{\lambda,\theta} \theta$$

$s.t$

$2.5\lambda_A + 4\lambda_B + 5\lambda_C + 7.5\lambda_D + 9\lambda_E + 7\lambda_F + 2.5\lambda_G + 5\lambda_H + 7.5\lambda_I \leq 7\theta$ (input x constraint)

$2.5\lambda_A + 2\lambda_B + 10\lambda_C + 11.5\lambda_D + 11.5\lambda_E + 5\lambda_F + 1\lambda_G + 4\lambda_H + 7\lambda_I \geq 5$(output y constraint)

$\lambda_A + \lambda_B + \lambda_C + \lambda_D + \lambda_E + \lambda_F + \lambda_G + \lambda_H + \lambda_I = 1$ (convexity constraint)

$\phi, \lambda_A, \lambda_B, \lambda_C, \lambda_D, \lambda_E, \lambda_F, \lambda_G, \lambda_H, \lambda_I \geq 0$ (non-negativity constraint)

The dataset is plotted in Fig. 1 with piece-wise linear frontier (VRS) associated with convexity and monotonicity property well-known in DEA. The convex VRS frontier is depicted by the segment GACDE and the free disposability lines showing monotonicity axiom.

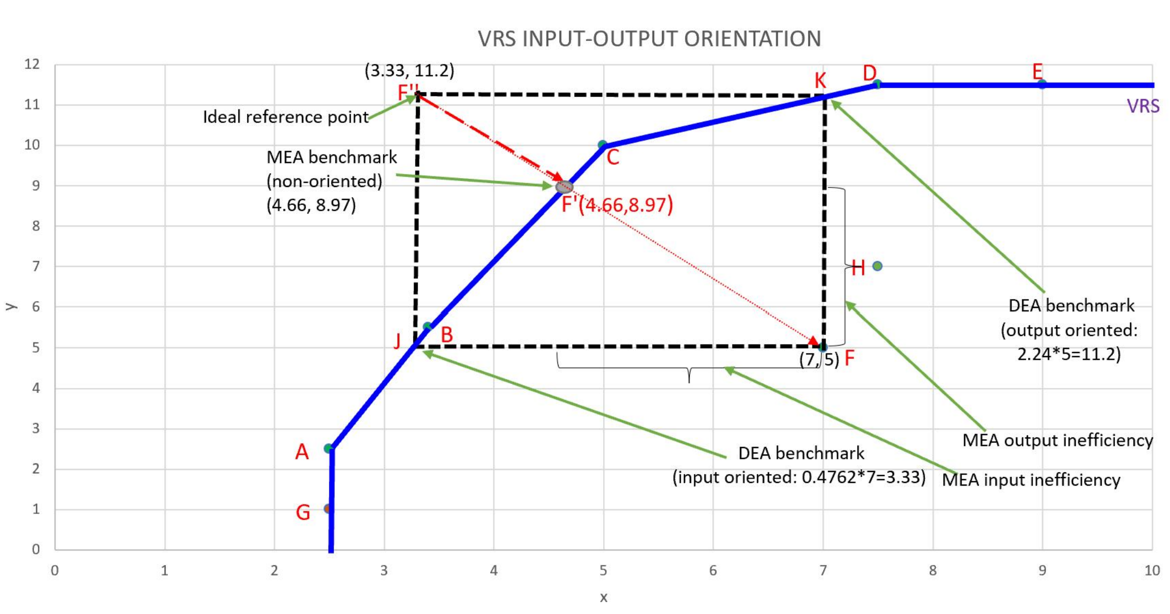

Figure 1:Illustrating MEA

Generally, the CCR (1978) DEA technical efficiency (TE) of a target DMU is defined as,

$$TE(x,y) = \frac{Distance\ from\ the\ origin\ to\ the\ VRS\ production\ frontier}{Distance\ from\ the\ origin\ to\ the\ unit}$$

As an example, the output-oriented DEA TE of DMU F is $TE_F(x,y) = \frac{11}{5} = 2.2$ and the input-oriented TE of this same DMU is $TE_F(x,y) = \frac{3.5}{7} = 0.5.$

The classical DEA efficiency score of DMU F is obtained by mathematically formulating and solving the following output oriented LPP:

The input-oriented LPP can be similarly formulated. The output-oriented scores for DMU F are ϕ_F=2.24, λ_A=0.14, λ_C=0.86 with $\lambda_{j=A-I,\, j\neq A,C}$=0,

,

Using similar definitions, the DEA input (Ei) and output (Eo) orientations of all DMUs are computed and presented in Table 2. This was programmed in R using the *Benchmarking* and *deaR* packages. The *R* codes are shown in appendix. In the table, we also show the slacks and targets or benchmarks under input-oriented efficiency measure. We find that DMU F is 47.6% efficient under input orientation and 224% under output orientation. The output-oriented DEA score means that DMU F is inefficient and hence, to be efficient, it should be able to raise all the outputs (5) radially to 224% of the current level (2.24×5=11.2) denoted as point K in the graph, without the need for extra inputs, whilst remaining in the production possibility set. Its input efficiency score of 47.6% means that, to be efficient, it should cut its input of 7 units to a target value of 3.33 (0.476×7) as in point J in Figure 1. DMU F is dominated by the frontier and hence, is inefficient. Five DMUs under input orientation identified are inefficient (B, E, F, H and I). Albeit DMU G is efficient (with a score of 1), it has an output slack of 1.5 units which was not incorporated in its score thereby over-estimating the score for DMU G. It is also observed that the efficiency scores can change depending on orientation used. One drawback of this DEA radial approach cannot *simultaneously* contract inputs and augment outputs.

Table 2a: DEA Input and output-oriented efficiency results

DMU	X	Y	Ei	Eo	Tari.x	Tari.y	sli.x	sli.y
A	2.5	2.5	1	1	2.5	2.5	0	0
B	4	2	0.625	3.5	2.5	2.5	0	0.5
C	5	10	1	1	5	10	0	0
D	7.5	11.5	1	1	7.5	11.5	0	0
E	9	11.5	0.833	1	7.5	11.5	0	0
F	**7**	**5**	**0.476**	**2.24**	**3.333**	**5**	**0**	**0**
G	2.5	1	1	2.5	2.5	2.5	0	1.5
H	5	4	0.6	2.5	3	4	0	0

I	7.5	7	0.533	1.6428	4	7	0	0

Figure 2b: Output-Oriented lambda values Across DMUs

DMU	**L1**	**L2**	**L3**	**L4**	**L5**	**L6**	**L7**	**L8**	**L9**
A	1.00	0	0.00	0	0	0	0	0	0
B	0.72	0	0.28	0	0	0	0	0	0
C	0.00	0	1.00	0	0	0	0	0	0
D	0.00	0	0.00	1	0	0	0	0	0
E	0.00	0	0.00	1	0	0	0	0	0
F	0.14	0	0.86	0	0	0	0	0	0
G	1.00	0	0.00	0	0	0	0	0	0
H	0.40	0	0.60	0	0	0	0	0	0
I	0.00	0	0.95	0.05	0	0	0	0	0

3.6 Multi-directional Efficiency Analysis (MEA)

The Multi-directional Efficiency Analysis (MEA) approach represents a significant advancement over traditional Data Envelopment Analysis (DEA) methodologies, offering a nuanced framework for assessing efficiency. Initially conceptualized by Bogetoft and Hougaard (1999a) and subsequently refined by Asmild et al. (2003b), MEA diverges from DEA's radial contraction or expansion approach by tailoring benchmarks to individual inputs and outputs, thus providing a more granular understanding of efficiency potentials (MEA Benchmark).

MEA's distinctive feature lies in its ability to identify proportional reductions in inputs or expansions in outputs based on each unit's efficiency improvement potential, thus rendering it particularly suited for scrutinizing efficiency patterns within each Decision Making Unit (DMU) independently (Asmild & Matthews, 2012; Bi et al., 2014; Wang et al., 2013b; Zhu et al., 2019;

Zhu et al., 2020). By prioritizing the examination of each variable's improvement potential in isolation, MEA excels in scenarios where DMUs aim to concurrently diminish certain inputs and undesirable outputs while enhancing desirable outputs.

In this study, we leverage MEA to its fullest potential, considering both desirable and undesirable outputs simultaneously. Our objective is twofold: to curtail input consumption and the emission of undesirable outputs, while concurrently augmenting the production of desirable outputs. Recognizing that efficiency enhancements may stem from a combination of input reduction, greenhouse gas emission mitigation, and GDP augmentation, we adopt a mixed-orientation MEA model. This model is specifically tailored to elevate GDP while concomitantly diminishing inputs and undesirable outputs.

By adopting this MEA approach with a mixed orientation, our study endeavors to foster sustainable development by optimizing resource utilization, mitigating environmental impacts, and bolstering economic output in a manner that aligns with the unique objectives of each DMU.

3.6.1 Formalising Multidirectional Efficiency Analysis

To formalize the MEA, a production technology that uses a vector of input *x* to produce vectors of output y (desirable) and c (undesirable). The technology set is given by:

$$\psi = \left\{ (x, y, c) \in \Re_{+}^{m+s_1+s_2} \middle| x \text{ can produce } y, c \right\} \quad (1)$$

The production technology ψ considers undesirable outputs as by-products since they are produced with desirable outputs(Bi et al., 2014b; Färe & Grosskopf, 2004). Three assumptions underpin the joint production technology for the asymmetric treatment of the desired and undesired outputs (Miao et al., 2019).

Strong or free disposability of desirable outputs:

If $(x, y, c) \in \psi$ and $y^* \leq y$, then $(x, y, c) \in \psi$. This assumption is like the classical assumption handling the disposability of desirable outputs. The axiom states that any output vector with a smaller desirable output is feasible if the observed desirable and bad outputs vectors are feasible. This assumption guides the strong free disposability of desirable outputs without any cost (Färe et al., 2005; Färe & Grosskopf, 2004).

Weak disposability of undesirable outputs (Shephard, 1970) **:**

If $\{(X, Y, C) \in L$ and $0 \leq \theta \leq 1$, then $(X, \theta Y, \theta C) \epsilon T\}.(X, \theta Y, \theta C) \epsilon T\}$. Weak disposability means that the proportional contraction of desirable and undesirable outputs is possible, hence for any given input, bad outputs can be reduced if and only if good inputs are also reduced in proportion. This axiom suggests that undesirable outputs cannot be freely disposed of, hence the sole reduction of undesirable outputs is impossible, due to their costly disposal which affects desirable outputs (Bogetoft & Hougaard, 1999b; Färe & Grosskopf, 2004)

Desirable and undesirable outputs being null-joint (Shephard, Ronald & Fare, 1944):

In the DEA framework, outputs can be classified as desirable (outputs we want to maximize) and undesirable (outputs we want to minimize, such as emissions). Following the null-joint assumption (Shephard, 1944; Fare et al., 2005), undesirable outputs are by-products of desirable outputs, meaning that the production of desirable outputs cannot be separated from undesirable outputs. In the context of energy efficiency, as countries increase desirable outputs such as GDP or industrial production, undesirable outputs such as CO_2 and CH_4 emissions are produced simultaneously.

Consistent with prior studies (Bi et al., 2014; Färe et al., 2005), the production technology ψ can be expressed as:

$$\psi = \left\{ (x, y, c) \,/\, \begin{array}{ll} x_i \geq \sum_{j=1}^{n} \lambda_j x_{ij}, & i = 1,2,\ldots,m \\ y_r \leq \sum_{j=1}^{n} \lambda_j y_{rj}, & r = 1,2,\ldots,s_1 \\ c_k \geq \sum_{j=1}^{n} \lambda_j c_{kj}, & k = 1,2,\ldots,s_2 \\ \sum_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0 & \end{array} \right\}$$

Where:

- x_i= inputs, $i = 1,\ldots,m$
- y_r= desirable outputs, $r = 1,\ldots,s_1$
- c_k= undesirable outputs, $k = 1,\ldots,s_2$
- λ_j= intensity weights for DMU j, $j = 1,\ldots,n$

This formulation ensures weak disposability of undesirable outputs and strong disposability of desirable outputs, which allows for realistic modeling of energy efficiency where reducing emissions may require reducing production proportionally.

In the DEA framework, λ_j represents the weights or intensity factors associated with each decision-making unit (DMU), while the constraint $\sum_{j=1}^{n} \lambda_j = 1$ ensures convexity of the production possibility set. The strong disposability of desirable outputs and weak disposability of undesirable outputs are enforced through the equality and inequality constraints on the good and bad outputs, respectively. This setup allows the model to realistically capture the trade-offs between producing desirable outputs and generating undesirable by-products, such as emissions in the context of energy efficiency.

Building on this, the Modified Energy Assessment (MEA) model is formalized following the approaches of Asmild and Matthews (2012) and Zhu (2019). The MEA is implemented in two stages. In the first stage, the Ideal Reference Point (IRP) is identified for each DMU. Specifically, for a given DMU_0 with inputs x_{i0}, desirable outputs y_{r0}, and undesirable outputs c_{k0}, the IRP is determined by solving the linear programming problem (LPP) that evaluates subvector efficiencies across the input, desirable output, and undesirable output dimensions.

Since the focus is on the reduction potential for inputs and undesirable outputs and the augmentation potential for desirable outputs, a non-oriented MEA model is employed. This approach allows for simultaneous assessment of the potential improvements in all dimensions of efficiency without privileging inputs over outputs, providing a comprehensive evaluation of energy efficiency performance across African states.

$$d_{i0}^{*} = \min_{\lambda_j, d_{i0}} d_{i0}$$

$$\begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij} \leq d_{i0}, \\ \sum_{j=1}^{n} \lambda_j x_{-ij} \leq x_{-io} \quad : \quad -i = 1, \dots, i-1, i+1, \dots, m \\ \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0} \quad : \quad r = 1, \dots, s_1 \\ \sum_{j=1}^{n} \lambda_j c_{kj} = c_{k0} \quad k = 1, \dots, s_2 \\ \sum_{j=1}^{n} \lambda_j = 1 \quad (if VRS), \\ \lambda_j \geq 0, \quad j = 1, \dots, n \end{cases} \tag{1}$$

$$\delta_{r0}^{*} = \max_{\lambda_j, \delta_r} \delta_{r0}$$

$$\text{s.t.} \begin{cases} \sum_{j=1}^{n} \lambda_j y_{rj} \geq \delta_{r0}, \\ \sum_{j=1}^{n} \lambda_j y_{-rj} \geq y_{-ro} \quad : \quad -r = 1, \dots, r-1, r+1, \dots, s_1 \\ \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{i0} \quad : \quad i = 1, \dots, m \\ \sum_{j=1}^{n} \lambda_j c_{kj} = c_{k0} \quad k = 1, \dots, s_2 \\ \sum_{j=1}^{n} \lambda_j = 1 \quad (if VRS), \lambda_j \geq 0, \quad \forall j = 1, \dots, n \end{cases} \tag{2}$$

$$\varphi_{i0}^{*} = \min_{\lambda_j, \varphi_k} \ \varphi_{k0}$$

$$\text{s.t.} \begin{cases} \sum_{j=1}^{n} \lambda_j c_{kj} = \varphi_{ko} \\ \sum_{j=1}^{n} \lambda_j c_{-kj} = c_{-k0}; \quad -k = 1, \dots, k-1, k+1, \dots, s_2 \\ \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{io} \ : \ i = 1, \dots, m \\ \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro}; \ r = 1, \dots, s_1 \\ \sum_{j=1}^{n} \lambda_j = 1 \ (if\, VRS), \lambda_j \geq 0, \ \forall j = 1, \dots, n \end{cases} \qquad (3)$$

In model (1)-(3), we consider a set of n DMU's $(j= 1,..., n)$ that produce s_1 of y desirable outputs ($r=1,..., s_1$) and s_2 of c undesirable outputs ($k=1,...s2$) using m of x inputs ($i=1,...,m$). The IRP $(d_{i0}^{*}, \delta_{r0}^{*}, \varphi_{i0}^{*})$ of the evaluated DMU $(d_{i0}, \delta_{r0}, \varphi_{i0})$ is then the optimal solutions of the estimated models (1)-(3). By estimating the IRP of each variable, the LPP, eqn (4), can be employed to ascertain the MEA efficiency of each variable of the assessed DMU.

$$\beta_0^* = \max_{\lambda_j, \beta_0} \left(\beta_{io} + \beta_{ro} + \beta_{ko}\right) (\quad)$$

$$\text{s.t.} \begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{io} - \beta_{io}\left(x_{io} - d_{io}^*\right), \quad i = 1, \ldots, m \\ \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro} + \beta_{ro}\left(\delta_{ro}^* - y_{ro}\right), \quad r = 1, \ldots, s_1 \\ \sum_{j=1}^{n} \lambda_j c_{kj} = c_{ko} - \beta_{ko}\left(c_{ko} - \varphi_{ko}^*\right), \quad k = 1, \ldots, s_2 \\ \sum_{j=1}^{n} \lambda_j = 1 \quad (if VRS), \\ \lambda_j \geq 0, \quad \forall j = 1, \ldots, n \end{cases} \quad \textbf{(4)}$$

Model (4) will then be used to finally determine the benchmark selection β_0 for the specific DMU which can be used to determine the MEA efficiency of each variable of the evaluated unit. $\beta_{r0}, \beta_{k0}, \beta_{i0}$ measures the proportion by which the desirable outputs are added while the undesirable outputs and inputs are contracted in the same proportion (G. Bi et al., 2014)

(Bi et al., 2014; Bogetoft & Hougaard, 1999; Kapelko & Lansink, 2017; Tziogkidis et al., 2020). β_{ij}, β_{rj} and β_{kj} always falls within the interval, $[0, 1]$ hence a DMU is said to have reached the frontier of the best practice firms if $\beta_{ij} = \beta_{rj} = \beta_{kj} = 0$ otherwise, the DMU is farther away from the frontier of the best practice firms (Asmild et al., 2003; Bi et al., 2014; Bogetoft &

Hougaard, 1999; Kapelko & Lansink, 2017). The optimal solution of model (4) is *(λ*,βi*,βr*,βk*)* and can be used to define the *relative variable-specific MEA efficiency* for each variable separately.

For the input variable x_{io} we can define specific input MEA efficiency as follows:

$$e_i = \frac{x_{io} - \beta^*_{i0}\left(x_{io} - d^*_{i0}\right)}{x_{io}} \quad (5)$$

For the desirable output y_{ro} we can define specific desirable output MEA efficiency as follows:

$$e_r = \frac{y_{ro}}{y_{ro} + \beta^*_{r0}\left(\delta^*_{r0} - y_{ro}\right)} \quad (6)$$

For the undesirable output $(c)_{ko}$, we can define specific undesirable output MEA efficiency as follows:

$$e_k = \frac{(c)_{ko} - \beta^*_{k0}\left(c_{ko} - \varphi^*_{k0}\right)}{c_{ko}} \quad (7)$$

where βo ⋆ is the value of the estimated benchmark from equation (4), Xi0 represent the specific input to be reduced, Yr0 represent the specific desirable output to be increased, the Ck0 represent the specific undesirable output to be reduced and di*… is the value of the ideal reference point that correspond with each of the observations respectively.

Using the variable-specific MEA efficiency values defined in equations (5) – (7) and based on the slack-based measure (SBM) model aggregation idea of Tone (2001), an integrated MEA efficiency is established consisting of all the input and output (desirable and undesirable) variables. Following (Asmild & Matthews, 2012; L. Zhu et al., 2019) Zhu et al. (2019), the holistic MEA efficiency score is given as:

$$\theta_0 = \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{\beta_{i0}^{*}\left(x_{i0} - d_{i0}^{*}\right)}{x_{i0}}}{1 + \frac{1}{s_1 + s_2}\left[\sum_{r=1}^{s_1}\frac{\beta_{r0}^{*}\left(\delta_{r0}^{*} - y_{ro}\right)}{y_{r0}} + \sum_{k=1}^{s_2}\frac{\beta_{k0}^{*}\left(c_{k0} - \varphi_{k0}^{*}\right)}{c_{k0}}\right]} \quad (8)$$

3.6.2 Illustrative example

Among other merits, the usefulness of the MEA approach is its ability to assess efficiency under non-orientation or both input and output orientation at the same time. We employ the original data set in Table 1 and the corresponding Figure 1 to demonstrate the MEA.

MEA for DMU F is executed in two stages. First, we identify the ideal reference point (IRP) by drawing a horizontal line (signifying input radial contraction potential) in a DEA fashion and a vertical line (signifying output radial augmentation potential) from the F coordinates until they hit the boundary of the convex production possibility set. Combining the improvement potentials in all of the dimensions (FJ, FK and KF'' and JF''), as in this graph, provides (typically unobtainable, optimal possible point) the IRP, F''(3.33, 11.2). Points J and K, where the DEA input contraction and output expansion intersect the frontier are the *DEA input and output benchmarks* or targets respectively. The intersection creates a diagonal distance FF'' which is an MEA non-radial line. Because the IRP, F'', is not within the PPS, the *MEA benchmark* for F in the direction of the ideal point is F'(4.66, 8.97).

Consequently, unlike DEA, MEA considers the shape of the part of the frontier that dominates the point and selects a benchmark that is proportional to the improvement potentials. In effect the MEA benchmark therefore has some desirable properties espoused by (Asmild et al., 2003a;

Bogetoft & Hougaard, 1999b) as explained earlier. For instance, whilst DEA selects weakly efficient benchmarks (E or G), MEA selects strongly efficient benchmarks (A or D). Consequently, unlike DEA, MEA considers the shape of the part of the frontier that dominates the point and selects a benchmark that is proportional to the improvement potentials. In effect the MEA benchmark therefore has some desirable properties espoused by (Asmild et al., 2003a; Bogetoft & Hougaard, 1999b) as explained earlier. For instance, whilst DEA selects weakly efficient benchmarks (E or G), MEA selects strongly efficient benchmarks (A or D).

Given the MEA equations (1) – (3), the MEA input-and-output specific efficiency scores for unit F are computed using the linear programs below while assuming a variable returns to scale technology.

Table 3: MEA Scores

Dmu	Xx	yy	IRPx	IRPy	PIPx	PIPy	inx	Iny	efx	efy	OE
A	0	0	2.5	2.5	2.5	2.5	0	Inf	1	1	0
B	1.5	5	2.5	7	3.21	4.63	0.2	0.76	0.8026316	0.4	0.1
C	0	0	5	10	5	10	0	Inf	1	1	0
D	0	0	7.5	11.5	7.5	11.5	0	Inf	1	1	0
E	1.5	0	7.5	11.5	7.5	11.5	0.2	Inf	0.8333333	1	0.1
F	3.666667	6.2	3.33	11.2	4.66	8.97	0.3	1.2609971	0.6650055	0.6	0.2
G	0	1.5	2.5	2.5	2.5	2.5	0	0.6666667	1	0.4	0
H	2	6	3	10	4	7	0.2	1.3333333	0.8	0.6	0.1
I	3.5	4.5	4	11.5	5.11	10.07	0.3	2.2814815	0.6818182	0.7	0.2

Note: xx= input excess

yy= shortfall

IRPx= input ideal reference point

IRPy= out ideal reference point

PIPx= input potential improvement point

PIPy= output potential improvement point

inx= input inefficiency

iny= output inefficiency

efx= input efficiency

efy= output efficiency

OE= overall efficiency

Stage 1: Find the ideal reference point for DMU F(7,5)

$$d_{iF}^{*} = \min_{\lambda_{j=A-I}, d_{iF}} d_{iF}$$

$$\text{s.t.}\begin{cases} 2.5\lambda_A + 4\lambda_B + 5\lambda_C + 7.5\lambda_D + 9\lambda_E + 7\lambda_F + 2.5\lambda_G + 5\lambda_H + 7.5\lambda_I \le 7d_{1F}: & i = 1 \\ 2.5\lambda_A + 2\lambda_B + 10\lambda_C + 11.5\lambda_D + 11.5\lambda_E + 5\lambda_F + 1\lambda_G + 4\lambda_H + 7\lambda_I \ge 5: & r = 1 \\ \lambda_A + \lambda_B + \lambda_C + \lambda_D + \lambda_E + \lambda_F + \lambda_G + \lambda_H + \lambda_I = 1 & \text{(if VRS)}, \\ \lambda_A + \lambda_B + \lambda_C + \lambda_D + \lambda_E + \lambda_F + \lambda_G + \lambda_H + \lambda_I \ge 0, & j = A, \ldots, I \end{cases}$$

$$\delta_{rF}^{*} = \max_{\lambda_{j=A-I}, d_{rF}} \delta_{rF}$$

$$\text{s.t.}\begin{cases} 2.5\lambda_A + 4\lambda_B + 5\lambda_C + 7.5\lambda_D + 9\lambda_E + 7\lambda_F + 2.5\lambda_G + 5\lambda_H + 7.5\lambda_I \le 7: & i = 1 \\ 2.5\lambda_A + 2\lambda_B + 10\lambda_C + 11.5\lambda_D + 11.5\lambda_E + 5\lambda_F + 1\lambda_G + 4\lambda_H + 7\lambda_I \ge 5\delta_{rF}: & r = 1 \\ \lambda_A + \lambda_B + \lambda_C + \lambda_D + \lambda_E + \lambda_F + \lambda_G + \lambda_H + \lambda_I = 1 & \text{(if VRS)}, \\ \lambda_A + \lambda_B + \lambda_C + \lambda_D + \lambda_E + \lambda_F + \lambda_G + \lambda_H + \lambda_I \ge 0, & j = A, \ldots, I \end{cases}$$

If there had been an undesirable output in this hypothetical data, we would have formulated the LPP for that. The LPP can be solved using excel solver or any LP software. Using R software with the Benchmarking package.

From the R output, the vertical and horizontal distance (along the diagonal path) toward the IRP is given by the me$direct command. This provides the excess inputs (output shortfalls) to subtract from (add to) actual inputs (outputs) to obtain the IRP. The IRP $(d_{io}^{*}, \delta_{ro}^{*}, \varphi_{io}^{*})$ for DMU F is thus computed as follows:

IRPx = actual input - excess input (input-orientation)

IRPy = actual output + output shortfall (output-orientation). In effect, we have:

$d_{1F}^{*}(\text{IRPx}) = 7 - 3.66667 = 3.3333$

$\delta_{1F}^{*}(\text{IRPy}) = 5 + 6.2 = 11.2$

Consequently, the ideal reference point for DMU F is $\left(d_{1F}^{*}, \delta_{1F}^{*}\right) = (3.33, 11.2)$. This implies that the largest possible contraction (augmentation) of input x (output y) is 3.33 (11.2) units. The weights of the peers of DMU F are 0.14 from peer unit A and 0.86 from peer unit C.

Still, the IRP is ideal and hence infeasible as it lies outside the boundary of the PPS. The step two in the MEA involves a second LP to move the IRP back to the frontier to determine the true MEA benchmark or the potential improvement point (PIP). This obviously explains the reason behind the different benchmark points selected by DEA as against MEA for an evaluated unit. The second LPP maximizes β_{0}^{*}, the proportion by which the inputs are contracted and/or the outputs are augmented to make the IRP possible and establish the MEA benchmark or the PIP.

$$\beta_{i0}^{*} = \min_{\lambda_{j=A-I}, \beta_{iF}} \left(\beta_{io}\right)$$

$$\text{s.t.}\begin{cases} 2.5\lambda_A + 4\lambda_B + 5\lambda_C + 7.5\lambda_D + 9\lambda_E + 7\lambda_F + 2.5\lambda_G + 5\lambda_H + 7.5\lambda_I \leq 7 - \beta_{io}(7 - 3.3333), \\ 2.5\lambda_A + 2\lambda_B + 10\lambda_C + 11.5\lambda_D + 11.5\lambda_E + 5\lambda_F + 1\lambda_G + 4\lambda_H + 7\lambda_I \geq 5, \\ \lambda_A + \lambda_B + \lambda_C + \lambda_D + \lambda_E + \lambda_F + \lambda_G + \lambda_H + \lambda_I = 1 \quad \text{(if VRS)} \\ \lambda_A + \lambda_B + \lambda_C + \lambda_D + \lambda_E + \lambda_F + \lambda_G + \lambda_H + \lambda_I \geq 0, \quad j = 1, \dots, 9 \end{cases}$$

$$\beta_{ro}^* = \max_{\lambda_{j=A-I}, \beta_{rF}} (\beta_{ro})$$

$$\text{s.t.}\begin{cases} 2.5\lambda_A + 4\lambda_B + 5\lambda_C + 7.5\lambda_D + 9\lambda_E + 7\lambda_F + 2.5\lambda_G + 5\lambda_H + 7.5\lambda_I \leq 7, \\ 2.5\lambda_A + 2\lambda_B + 10\lambda_C + 11.5\lambda_D + 11.5\lambda_E + 5\lambda_F + 1\lambda_G + 4\lambda_H + 7\lambda_I \geq 5 + \beta_{ro}(11.2 - 5), \\ \lambda_A + \lambda_B + \lambda_C + \lambda_D + \lambda_E + \lambda_F + \lambda_G + \lambda_H + \lambda_I = 1 \quad \text{(if VRS)} \\ \lambda_A + \lambda_B + \lambda_C + \lambda_D + \lambda_E + \lambda_F + \lambda_G + \lambda_H + \lambda_I \geq 0, \quad j = 1, \dots, 9 \end{cases}$$

The optimal solution to the above LPP are the lambdas and beta values (λ^*, β_0^*). In *R* software, the beta values, β_0^*, are the MEA input and output-specific inefficiencies. Hence, the MEA benchmark or PIP is given by,

$$PIP_x = x_{io} - \beta_{io}\left(x_{io} - d_{io}^*\right)$$

$$PIP_y = y_{ro} + \beta_{ro}\left(\delta_{ro}^* - y_{ro}\right)$$

where d_{io}^* and δ_{ro}^* are the input and output coordinates of IRP respectively. For DMU F, the PIP is given by,

$$PIP_{x,F} = 7 - 0.6395(7 - 3.333) = 4.655$$

$$PIP_{y.F} = 5 + 0.6395(11.2 - 5) = 8.965$$

The MEA benchmark or potential improvement point for DMU F can easily be observed at point F'(4.66, 8.97) on the DEA frontier which is feasible unlike the IRP. This means that DMU F will be MEA efficient when it uses 4.66 units of input x to produce 8.97 units of output y.

The relative input-specific and output-specific (x, y) MEA efficiency scores for DMU F are computed as:

$$e_{iF} = \frac{x_{io} - \beta_{io}^*\left(x_{io} - d_{io}^*\right)}{x_{io}} = \frac{PIP_x}{x_{io}} = \frac{4.655}{7} = 0.665$$

$$e_{rF} = \frac{y_{ro}}{y_{ro} + \beta_{ro}^*\left(\delta_{ro}^* - y_{ro}\right)} = \frac{y_{ro}}{PIP_y} = \frac{5}{8.965} = 0.558$$

DMU F is simultaneously 66.5% efficient in the utilization of the input variable and 55.8% efficient in output augmentation whilst accounting for all slacks. These are termed the patterns of efficiency(Asmild & Matthews, 2012). One minus these efficiency scores should deliver inefficiency scores.

Finally, the integrated, comprehensive or overall, MEA non-oriented efficiency score for unit F is given as

$$\theta_0 = \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{\beta_{i0}^*\left(x_{i0} - d_{i0}^*\right)}{x_{i0}}}{1 + \frac{1}{s_1 + s_2}\left[\sum_{r=1}^{s_1}\frac{\beta_{r0}^*\left(\delta_{r0}^* - y_{r0}\right)}{y_{r0}} + \sum_{k=1}^{s_2}\frac{\beta_{k0}^*\left(c_{k0} - \varphi_{k0}^*\right)}{c_{k0}}\right]}$$

$$\theta_F = \frac{1 - \frac{1}{1}(0.665 + 0)}{1 + \frac{1}{1+0}[0.558 + 0]}$$

$$\theta_F = 0.215$$

This implies that much of the low 22% efficiency of DMU F emanates from the low efficiency on the output than on the input side. Table 3 show the complete results of m$ direct scores, ideal reference points, potential improvement points, MEA integrated efficiency scores, MEA input-and-output-specific efficiency and inefficiency scores for all the hypothetical DMUs.

It is observed that the outputs of some of the DMUs exhibit LP infeasibilities because the ideal reference point projection and MEA benchmark of the observed variable is located outside the boundary of the PPS

3.7 Second Stage Regression

Léopold Simar and Wilson (2007, 2011, and 2015) extensively investigated various second-stage DEA regressions found in the literature. They argued that since true DEA efficiencies are unobservable, they must be replaced with DEA efficiency estimates, which are inherently correlated. The deterministic nature of DEA stems from its capacity to account for random noise introduced by data or measurement errors. However, this approach is sensitive to outliers and sampling variations, making it challenging to solely rely on efficiency estimates for statistical inferences, such as forming judgments about population parameters and the reliability of statistical relationships, typically based on random sampling (Daraio & Simar, 2007). Furthermore, ignoring environmental variations directly impacts firm performance, leading to biased performance measurements (Dyson et al., 2001). Therefore, it is advisable to include sensitivity analysis to evaluate the robustness of DEA efficiency scores (Wang et al., 2019) and the effects of key external factors believed to be beyond management control but can influence first-stage estimates (Fried, Lovell, Schmidt, & Yaisawarng, 2002).

Consequently, many energy efficiency studies have employed different second-stage regression models to assess the impact of environmental variables on efficiency and dynamic productivity indices and to ensure consistent parameter estimation. Notably, some studies have utilized Tobit or OLS regressions (Amowine et al., 2019; Apergis et al., 2015; Borozan, 2018; Honma & Hu, 2008; Hong, & Fang, 2015; Ren, Gao, Zhang, & Chen, 2020b; Zeng et al., 2020; Zhang et al., 2011). However, Simar and Wilson (2007), as cited by (Ohene-Asare et al., 2020), criticized the Tobit model for "suffering from serial correlation and lacking a proper data generating process, leading to biased estimates." Consequently, when such assumptions are not met, regression coefficients may appear statistically significant, leading to misguided decisions.

Banker and Natarajan (2008, pg. 58) argue that "OLS is more robust and appropriate for evaluating the impact of contextual variables on dynamic productivity than Simar and Wilson's truncated bootstrapped regressions, which are valid only under much more restrictive assumptions about the data-generating process." Nevertheless, Simar and Wilson's recommended bootstrapped-truncated regression has also been widely applied in energy efficiency studies based on efficiency scores estimations (Amowine et al., 2019; Lee et al., 2011a; Ohene Asare et al., 2020; Song et al., 2013). However, since the CMPI scores used in this study are not technically truncated but positive integers, the truncated bootstrapped regression is not required. Therefore, the current study comparatively adopts pooled OLS, fixed effect, random effect, Beck & Katz for panel-corrected standard errors, Driscoll & Kraay SCC, the two-stage least squares method, and the two-steps system GMM regression models to methodologically crosscheck and test the robustness of the second-stage DEA regression methods.

3.7.1 The entire regression model based on regression output

In the study, the first stage energy efficiency indices serve as the dependent variable, elucidating each country's level of energy efficiency. This variable is explicated by a multitude of environmental factors, including undesirable emissions such as CO2 and CH4, regional bloc affiliation (EAC, ECOWAS, AMU, ECCAS, and SADC), economic indicators like recession and economic development, technological advancement, inflation rate, population size, renewable energy utilization, foreign direct investment, degree of government intervention in economic activities, and the extent of urbanization.

These environmental factors, derived from extensive literature review and meticulously sampled through correlation analysis, represent key determinants influencing energy efficiency within African states. To ensure the robustness and reliability of our findings, we subject these variables to a comprehensive array of econometric techniques, validating their significance and impact on energy efficiency outcomes. Through meticulous regression analysis, we derive estimates that shed light on the intricate relationships between these environmental factors and energy efficiency indices. This empirical approach enables us to discern the relative influence of each factor and elucidate the mechanisms driving energy efficiency trends across African countries.

By employing sophisticated econometric methodologies and leveraging a diverse set of environmental variables, the study aims to provide a comprehensive understanding of the complex dynamics shaping energy efficiency patterns in the African context. Through rigorous analysis and interpretation of regression estimates, the study seeks to contribute valuable insights to the discourse on sustainable development and environmental stewardship in the region.

$$\begin{aligned} \mathrm{EE}_{it} = \beta_0 + \beta_1\mathrm{POP}_{it} + \beta_2\mathrm{CO2}_{it} + \beta_3\mathrm{CH4}_{it} + \beta_4\mathrm{TECH}_{it} + \beta_5\mathrm{REN}_{it} + \beta_6\mathrm{INF}_{it} + \beta_7\mathrm{ED}_{it} \\ + \beta_8\mathrm{FDI}_{it} + \beta_9\mathrm{GOV}_{it} + \beta_{10}\mathrm{URB}_{it} + \beta_{11}\mathrm{BLOCEAC}_{it} + \beta_{12}\mathrm{BLOCECCAS}_{it} \\ + \beta_{13}\mathrm{BLOCECOWAS}_{it} + \beta_{14}\mathrm{BLOCSADC}_{it} + \mu_{it} \end{aligned}$$

Where:

- EE_{it}= energy efficiency of country $i$at time t
- β_0= intercept
- $\beta_1, \beta_2, \ldots, \beta_{14}$= parameters to be estimated
- μ_{it}= error term capturing unobserved effects

Explanatory variables:

- **POP:** Population of the state (millions)
- **CO2:** Carbon dioxide emissions (kiloton)
- **CH4:** Energy-related methane emissions
- **TECH:** Level of technology (capital-labour ratio)
- **REN:** Renewable energy consumption as proportion of total energy consumed
- **INF:** Annual inflation rate
- **ED:** Economic development (GNI per capita)
- **FDI:** Foreign direct investment (% of GDP)
- **GOV:** Government intervention (% of government consumption to GDP)
- **URB:** Urbanization (% of population in urban areas)

- **BLOCEAC, BLOCECCAS, BLOCECOWAS, BLOCSADC:** Dummy variables representing membership in major African regional blocs (1 = member, 0 = otherwise)

Notes:

1. This is a panel regression model, allowing the assessment of both cross-country and over-time variations in energy efficiency.
2. The coefficients β_i measure the marginal impact of each explanatory variable on energy efficiency.
3. The model can accommodate fixed effects or random effects depending on the results of the Hausman test.
4. This specification addresses the objectives of analyzing energy efficiency patterns, external determinants, and differences across regional blocs.

3.8 Simar-Zelenyuk-Adapted-Li test

A typical area of research for many empirical studies in the area of efficiency and productivity analysis is to compare the efficiencies of various groups in an industry or region or across time for the same groups. One way to approach this issue which is becoming more and more popular in many applied areas is the use of the Simar-Zelenyuk-Adapted Li test (SZAL). The Li test was proposed by (Li, 1996) and adapted by (Simar & Zelenyuk, 2006) into the DEA context which is referred to as SZAL. Unlike other tests such as Mann-Whitney U test or Kruskal-Wallis the Friedman test, it does not strictly need the selection of a dependent or independent sample. Other methods just evaluate the central tendencies and presume that the real efficiency estimates are seen when they are in fact unknown. The SZAL test tackles these difficulties by comparing the complete distributions of efficiency scores between various groups using kernel density estimations and bootstrapping processes (Epure et al., 2011; Simar & Zelenyuk, 2006).

This research uses the SZAL to statistically explore differences in the distribution of efficiency or frontier estimates between the different regional blocs of Africa (Simar & Zelenyuk, 2006). This non-parametric test will effectively compare the equality of distributions of the efficiency estimates using Kernel density estimations. To determine the potential differences in efficiency estimates under different subgroups that is the regional blocs, we test the following hypotheses given the efficiency estimates of two groups expressed as two density functions $f_{G1}\left(\rho^{G1}\right)$ and $f_{G2}\left(\rho^{G2}\right)$.

$$H_0: f_{G1}\left(\rho^{G1}\right) = f_{G2}\left(\rho^{G2}\right)$$

$$H_A: f_{G1}\left(\rho^{G1}\right) \neq f_{G2}\left(\rho^{G2}\right)$$

The null says that the density of efficiency estimates is the same between the two groups, implying that the two groups perform similarly. The alternative says that the distribution of efficiency estimates is different between the two groups. The left and righthand sides of the equal to sign are the probability distributions whilst the terms in the brackets are the efficiency scores.

3.9 Test of Return to Scale Properties

Data Envelopment Analysis (DEA) is widely used to evaluate efficiency and has provided essential insights for policymakers and analysts, particularly in energy efficiency studies (Mardani et al., 2017; Yu & He, 2020). A key assumption in DEA is the choice of returns to scale (RTS), as different RTS assumptions can lead to different efficiency conclusions. Returns to scale measure how changes in inputs affect outputs, indicating whether proportional changes in inputs lead to proportional changes in outputs.

According to Simar and Wilson (2002), the RTS assumption, whether constant returns to scale (CRS) or variable returns to scale (VRS), is critical in efficiency studies. Choosing the wrong RTS can bias efficiency estimates and reduce statistical reliability. CRS assumes a proportional change in outputs for a proportional change in inputs, while VRS allows for non-proportional changes, capturing scale inefficiencies.

To select the appropriate RTS, this study employs the non-parametric RTS test of Simar (2011). The hypotheses are:

H_0: ψ exhibits global CRS
H_1: ψ exhibits VRS

Simar & Wilson (2002, 2011) propose three distinct test statistics to evaluate RTS:

1. **Mean of ratios ($\hat{S}_1$):** Measures the average distance between CRS and VRS efficiency scores in an input-oriented direction. Formally:

$$\widehat{S}_1 = \frac{1}{N}\sum_{j=1}^{N}\frac{\mathrm{CRS}_j}{\mathrm{VRS}_j}$$

2. **Ratio of means ($\hat{S}_2$):** The sum of CRS efficiency scores divided by the sum of VRS efficiency scores:

$$\widehat{S}_2 = \frac{\sum_{j=1}^{N}\mathrm{CRS}_j}{\sum_{j=1}^{N}\mathrm{VRS}_j}$$

3. **Mean of ratios minus 1 ($\hat{S}_3$):** The average of the individual CRS-to-VRS ratios minus 1:

$$\widehat{S}_3 = \widehat{S}_1 - 1$$

These three statistics allow the researcher to determine whether CRS or VRS is more appropriate for the dataset, ensuring that efficiency estimates are unbiased and accurately reflect the production technology.

3.10 Input and Output Variables

3.10.1 Inputs

a. Labour

The study employs the total labour force, measured in millions, as a proxy for labour input. The labour force encompasses individuals aged 15 and older who actively contribute their labour to the production of goods and services within a specified period in a country. Compensation, measured in US dollars ($), is utilized as the price of labour. It includes all forms of payments, both in cash and in kind (such as food and housing), provided to employees in exchange for the services they render. Additionally, government contributions to social insurance schemes, such as social security and pensions, which offer benefits to employees, are considered part of the compensation package (International Energy Agency & Bank, 2014).

This approach ensures that the study captures the significant role of labor input in the production process and accounts for the various forms of remuneration received by workers, including both monetary and non-monetary benefits.

b. Energy used

In this study, energy used is quantified in quadrillion British thermal units (quad BTU). The selected energy input for analysis is total primary energy use, which represents the utilization of primary energy before its conversion into other end-use fuels. This encompasses the consumption of various energy sources, including crude oil, coal, natural gas, nuclear energy, and other renewables, throughout the periods examined.

To facilitate analysis, the prices of these diverse energy forms were standardized. This standardization ensures a consistent comparison of energy prices across countries and time frames. Consequently, a yearly average price was computed for each country, serving as the proxy for the energy price in the study. By employing total primary energy use as the energy input and incorporating standardized energy prices, the study aims to explore the relationship between energy consumption and other variables under scrutiny.

This methodology allows researchers to investigate the impact of energy usage on diverse economic and environmental indicators. It is essential to highlight that the selection of energy input and the standardization of energy prices are pivotal steps in conducting a thorough analysis of energy-related factors. These considerations guarantee the accuracy and comparability of the data, facilitating meaningful insights into the nexus between energy consumption, economic variables, and environmental outcomes.

c. Capital service

The concept of capital service embodies the flow of productive services generated by an asset utilized in the production process. It represents the tangible contribution of capital assets to the overall productivity of a specific state or economy over a defined period. Although alternative measures of capital, such as gross and net capital stocks, exist, they fail to accurately capture the productive efficiency of the asset. As per recommendations from the Organization for Economic Co-operation and Development (OECD), the most suitable measures for analyzing capital as an input and its price for productivity and production analysis are capital service and user costs of capital. However, data collection for capital services can pose challenges, leading many studies to utilize stocks of assets as a proxy for capital's productivity contribution (Hu & Kao, 2007; Li & Tao, 2017; Lin & Zhang, 2017).

In this context, this study holds significance as it utilizes data from the Penn World Table (PWT 9.1 version) to employ the quantity of capital services and user cost as indicators for capital input and its price in estimations of total factor productivity growth and productivity analysis. By embracing these measures, the study aims to offer a comprehensive understanding of the role of capital assets in productivity and to illuminate the relationship between capital and economic performance.

3.10.2 Outputs

a. GDP

Gross Domestic Product (GDP) serves as a comprehensive measure of the total value added by all resident producers within a country's borders. It encompasses the sum of gross value added by various economic activities, including any product taxes but excluding subsidies not accounted for in the value of products (Adom et al., 2018). In the context of efficiently utilizing energy resources, the fundamental objective has often been to enhance GDP, which serves as a key indicator of aggregate output and overall economic productivity levels (Geller et al., 2006; Winkler, 2005).

Consistent with existing literature on energy efficiency (International Energy Agency & Bank, 2014; Vardy et al., 2017; Wright et al., 2013), real GDP measured in millions of United States dollars is employed as the proxy for economic output in this study. The use of real GDP as a proxy for economic output ensures a standardized and widely accepted measure for assessing the impact of energy efficiency on overall economic performance.

b. CO2

Carbon dioxide (CO2) emissions serve as a crucial proxy for undesirable output, offering insights into the environmental impact of energy consumption. These emissions are typically estimated by analyzing the breakdown of energy consumption across various fuel categories, including coal, coke, crude oil, gasoline, kerosene, diesel oil, fuel oil, and natural gas.

The burning of fossil fuels, such as coal, oil, and gas, releases carbon dioxide into the atmosphere, contributing to climate change and global warming by trapping heat and leading to the greenhouse effect. Consequently, monitoring and managing CO2 emissions have become imperative in mitigating the adverse effects of climate change.

To estimate CO2 emissions accurately, researchers and policymakers scrutinize energy consumption patterns and the relative contributions of different fuel types. By quantifying the consumption of each fuel category, it becomes possible to calculate the associated CO2 emissions.

These estimations play a pivotal role in enabling governments, organizations, and researchers to track and evaluate the environmental impact of energy use. They facilitate the identification of sectors or industries with high carbon footprints, the development of strategies for reducing emissions, and the implementation of policies to promote cleaner and more sustainable energy sources.

By utilizing CO2 emissions as a proxy for undesirable output, decision-makers can assess the environmental performance of various sectors, evaluate the effectiveness of emission reduction measures, and collaborate towards building a more sustainable and environmentally friendly future.

Table 4: Variable Definitions and Description

	Variable	Symbol	Proxy	Application
Inputs	Labour	x1	Number of persons engaged (Million)	Lin & Sai, 2022; Ohene-Asare et al. 2020; Vardy et al., 2017 Wang, Wei & Zhang, 2012
	Energy Used	x2	Total primary energy consumed (quadrillion bitumen)	Ohene-Asare et al. 2020 Apergis et al. 2015 Wang, Wei & Zhang, 2012

	Capital Service	x3	Capital services at constant national price (2011=1)	Amowine et al., 2019; Ball, Färe, rosskopf, & Zaim, 2005; Rakshit et al., 2020; Tone & Tsutsui, 2007; Tzu-Chun, Kai-Ping, & Yung-Lieh, 2012; Wang et al., 2019; Zhang et al., 2011
Outputs	Real GDP	y1	Real GDP at constant 2011national price (in Million 2011 US$)	Adom et al., 2018 Weng 2013 Ohene-Asare et al., 2020 Lin & Sai, 2022 Mohd Alsaleh & Abdul-Rahim, 2018; Chatzistamoulou et al., 2019; Honma & Hu, 2014
	CO_2 Emission	y2	Total CO_2 emissions (Undesirable output)	Ohene-Asare et al. 2020; Li & Lin, 2015; Zhou & Ang, 2008; Ohene-Asare et al, 2020; Zhang et al., 2011; Chatzistamoulou, Kounetas, & Tsekouras, 2019; Ren & Yu 2020

Source: Author's Computation

3.11 Instruments for data analysis

Data used in the study is analyzed using both basic descriptive and inferential statistics. The statistical results are generated using R version 4.1.2 in conjunction with the Benchmark package version 0.29. Excel is also used in analyzing descriptive statistics and hypothesis testing.

3.12 Conclusion

The chapter provides a thorough overview of the data collection procedure and the diverse methodologies utilized to achieve the study's goals. Hypothetical data served as the foundation for estimating variable-specific inefficiencies, efficiencies, and overall efficiency scores using the MEA approach. Additionally, the chapter undertook the estimation of efficiency scores employing the DEA method.

CHAPTER FOUR

DATA ANALYSIS AND DISCUSSION OF FINDINGS

4.1 Introduction

This chapter delves into the culmination of data analysis, engaging both empirical evidence and theoretical frameworks to accomplish the study's objectives and address pertinent inquiries. It commences with an exposition of descriptive statistics concerning inputs and outputs, alongside their correlations, aimed at scrutinizing the isotonicity property of the data.

Furthermore, to ascertain the true technological landscape underpinning the energy industry in Africa, the investigation employs Simar and Wilson's (2002) test of returns to scale, elucidating the findings. Additionally, the chapter assesses the MEA efficiency across all countries spanning the period from 2000 to 2019.

Subsequently, the analysis delves into regression outcomes, probing the impact of undesirable outputs, regional bloc affiliations, and other pertinent control variables on the energy utilization of African nations. Employing state-of-the-art econometric techniques, this segment aims to provide robust insights into the intricate dynamics at play within the African energy landscape.

4.2 Description of data

The chapter underscores that the dataset utilized for the study constitutes a cross-country examination of African nations, drawing from an unbalanced sample comprising 32 countries. These selections were made based on data availability spanning the period from 2000 to 2019. Encompassing a diverse representation, the sample comprises 5 countries from the Arab Maghreb Union (AMU), 5 from the East African Community (EAC), 6 from the Economic Community of Central African States (ECCAS), 9 from the Economic Community of West African States (ECOWAS), and 7 from the Southern African Development Community (SADC).

This strategic sample composition facilitates a thorough analysis of efficiency levels across various regional organizations within the African context, offering comprehensive insights into the energy dynamics across the continent.

The Table 5 provides a comprehensive overview of the dataset, focusing on key variables related to the energy industry, economic performance, and environmental impact across various African countries.

The mean capital service expenditure across the sample is approximately $2835.82 million, with a considerable standard deviation of $6086.9 million. This indicates a wide dispersion in capital service investment among the countries in the dataset. The mean expenditure on labour is relatively lower compared to capital, with an average of $7.26 million and a standard deviation of $10.25 million. However, the dispersion is still notable. On average, countries in the dataset utilize 0.4 quadrillion btu of energy, with a standard deviation of 1.08 quadrillion btu. This variable also exhibits significant variability across countries. The mean GDP stands at approximately $109,293 million, with a high standard deviation of $220,757.8 million, suggesting substantial disparity in economic output among the countries. The mean CO2 emissions amount to 29,712.12 kt, with a substantial standard deviation of 84,765.14 kt, indicating significant divergence in carbon emissions across the sample.

The F-statistics for years and groups provide insights into the significance of differences across time periods and groups (likely countries) respectively. For Capital Service, Labour, GDP, and CO2 emissions, the F-statistics for both years and groups are statistically significant at varying levels, indicating that there are significant differences in the means of these variables across both time periods and groups. Energy Used shows statistically significant differences across groups but not across years, suggesting that energy usage patterns vary significantly among different countries or regions but remain relatively consistent over time.

The wide dispersion in the values of capital service, labour, energy use, GDP, and CO2 emissions highlights the heterogeneity among African countries in terms of economic development, industrialization, and environmental impact. The significant F-statistics for both years and groups underscore the importance of considering both temporal and geographical variations when analyzing energy-related variables and their impacts. The substantial standard deviations for all variables suggest the presence of outliers or extreme values in the dataset, which may warrant further study to understand the factors driving such disparities. The varying levels of statistical significance across variables and between years and groups indicate the complex interplay of economic, social, and environmental factors influencing energy dynamics in African countries.

Table 5: Summary Statistics of Pooled data (2000-2019)

	N		**Capital Service (million US$)**	**Labour (millions US$)**	**Energy used (quadrillion btu)**	**GDP (millions US$)**	**CO2 emissions (kt)**
Pooled		Mean	2835.82	7.26	0.4	109293	29712.12
	640	Sd	6086.9	10.25	1.08	220757.8	84765.14
		Min	3.14	0.04	0	374.08	47.67
		Max	32363.46	73.02	5.73	1287589	503112.4
Year		F- Stat	16.6***	7.617**	1.991	9.963**	1.235
Groups		F- Stat	6.048***	7.736***	20.79***	18.74***	17.28***

'*', '**', '*', '.' denote significance at 0.1%, 1%, 5% and 10% respectively**

The Table 6 provides insights into the relationships between various variables in the dataset, shedding light on how changes in one variable correspond to changes in another.

The correlation coefficients range from -1 to 1, where: Values close to 1 indicate a strong positive relationship (as one variable increases, the other tends to increase). Values close to -1 indicate a strong negative relationship (as one variable increases, the other tends to decrease). Values close to 0 indicate little to no linear relationship between the variables. All correlations are significant at various levels (0.1%, 1%, 5%, and 10%).

Capital Service shows strong positive correlations with Labour (0.834), Energy Used (0.703), GDP (0.866), and CO2 Emissions (0.718). This suggests that higher capital service expenditures are associated with increased labour input, energy consumption, economic output (GDP), and carbon emissions. Labour also exhibits strong positive correlations with Energy Used (0.449), GDP (0.789), and CO2 Emissions (0.438), albeit to a slightly lesser extent compared to Capital Service. This indicates that higher labour inputs tend to coincide with higher energy consumption, GDP, and carbon emissions. Energy Used demonstrates moderate positive correlations with Capital Service (0.703), Labour (0.449), GDP (0.819), and CO2 Emissions (0.988). This indicates that higher energy usage is associated with increased capital service expenditures, labor inputs, economic output, and carbon emissions. GDP and CO2 Emissions exhibit strong positive correlation (0.772), indicating that higher economic output tends to coincide with increased carbon emissions.

The strong positive correlations between Capital Service, Labour, Energy Used, GDP, and CO2 Emissions suggest interdependencies among these variables within the context of the energy industry and economic development. The relationships observed highlight the intricate nexus between investment, labour, energy consumption, economic growth, and environmental impact.

Higher levels of capital service and labour inputs tend to drive increased energy consumption and economic output, which, in turn, can lead to higher carbon emissions. The significant correlations underscore the need for integrated policies and strategies that address energy efficiency, sustainable development, and environmental conservation simultaneously.

Table 6: Correlation Matrix

	Capital Service	*Labour*	*Energy Used*	*GDP*	*CO2 Emission*
Capital Service	1.000				
Labour	0.834	1.000			
Energy Used	0.703	0.449	1.000		
GDP	0.866	0.789	0.819	1.000	
CO2 Emission	0.718	0.438	0.988	0.772	1.000

'', '**', '*', '.' denote significance at 0.1%, 1%, 5% and 10% respectively***

The Table 7 presents the results of tests of returns to scale, which aim to determine whether a production process exhibits constant returns to scale (CRS), increasing returns to scale (IRS), or decreasing returns to scale (DRS).

The null hypothesis (Ho) states that the production process is characterized by constant returns to scale (CRS), implying that doubling the inputs will double the outputs. The significance level indicates the threshold at which the results are considered statistically significant.

(S1) Mean of Ratios represents the average of the calculated ratios of outputs to inputs for each observation. (S2) Ratio of Means is the ratio of the mean output to the mean input across all observations. (S3) Mean of Ratios minus 1 value is calculated by subtracting 1 from the mean of the ratios, which is expected to be 0 if the production process exhibits constant returns to scale.

The test statistic compares the calculated mean of ratios to critical levels to determine whether to reject the null hypothesis. The critical levels represent thresholds at which the null hypothesis would be rejected, indicating significance levels of 5% and 1%.

For the test statistic, the values are provided along with significance indicators (***p<0.1%, **p<1%, *p<5%, and p<10%), denoting the level of significance at which the null hypothesis is rejected. The critical levels provide benchmarks for comparison. If the test statistic exceeds these critical values, the null hypothesis is rejected. In this case, the test statistic exceeds the critical levels for all three measures (S1, S2, and S3) at the 5% significance level, indicating that the null hypothesis of constant returns to scale (CRS) is rejected. The test suggests that the production process is not characterized by constant returns to scale, implying that doubling the inputs does not lead to a proportional increase in outputs.

The results suggest that the production process may exhibit either increasing or decreasing returns to scale, indicating that the relationship between inputs and outputs is not linear. This finding has implications for production planning, resource allocation, and efficiency optimization within the context of the energy industry. Further study may be done to understand the specific factors driving the observed returns to scale and to identify opportunities for improving productivity and sustainability in the energy sector.

Table 7: Tests of returns to scale

Ho: μ is CRS	**Significance level**	**Mean of ratios** (S1)	**Ratio of means** (S2)	**Mean of ratios minus 1** (S3)	**Conclusion**
Test Static		0.9298467***	0.4620527*	-0.06705516***	
Critical Level	5%	0.9664829	0.6381129	-0.02658735	Reject Ho
Critical Level	1%	0.9626069	0.3377091	-0.02647794	

*****p<0.1%, **p<1% and *p<5% and p<10%**

The Fig 2 presents data for various variables across different years, providing insights into trends and patterns over time within the energy industry. Both capital service and labour inputs generally show an increasing trend over the years. This suggests that there has been a consistent investment in capital and labour within the energy industry, possibly indicating growth or expansion. The amount of energy utilized also demonstrates an increasing trend, albeit with fluctuations. This could indicate an increasing demand for energy resources over time, reflecting economic growth and development. Gross Domestic Product shows a steady increase over the years, reflecting overall economic growth within the countries under observation. This aligns with the trends observed in capital service, labor, and energy usage. CO2 emissions display fluctuations over the years, possibly influenced by various factors such as economic activity, industrial processes, and environmental policies.

By comparing the variables across different years, it is possible to identify correlations and potential causal relationships. For example, increases in capital service and labour inputs may contribute to higher energy usage, which in turn could lead to increased economic output (GDP) but also higher carbon emissions (CO2).

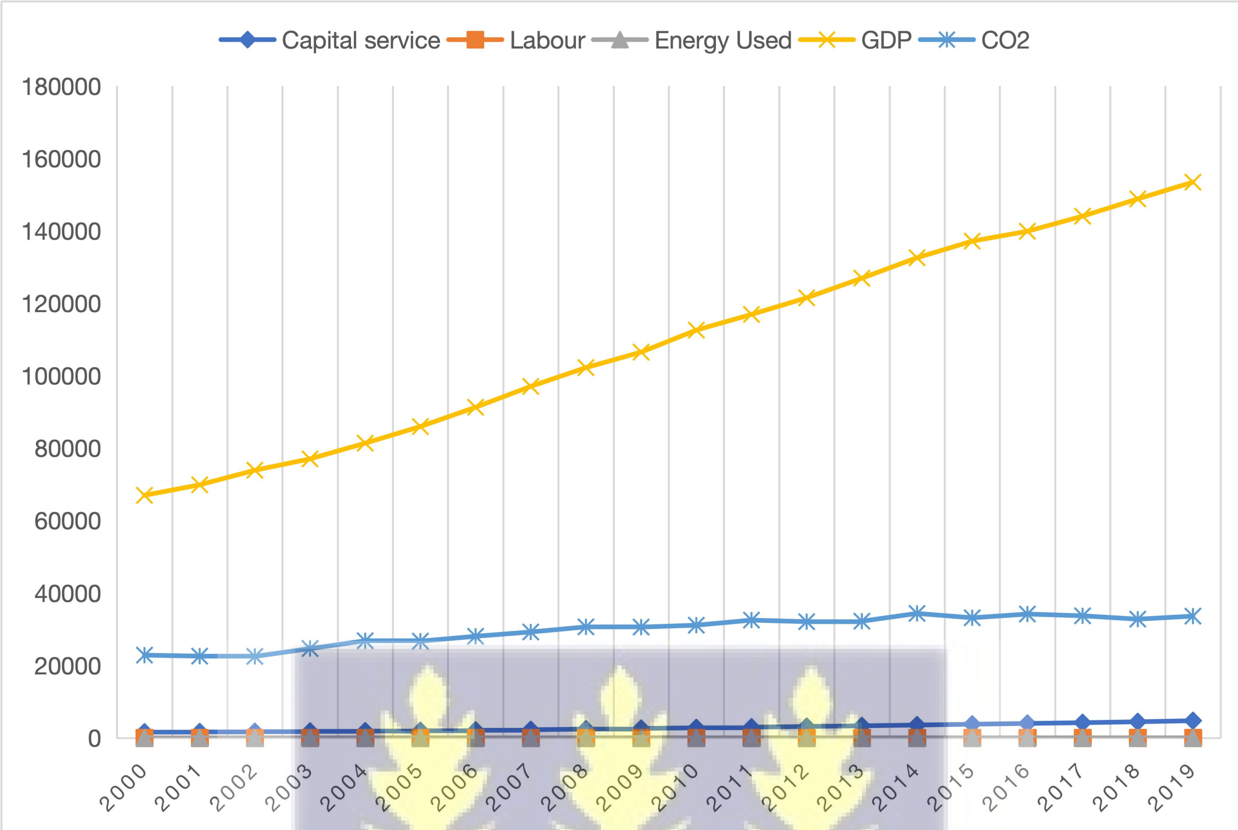

Figure 2: Trend of the Input and Output Variables

4.3 Environmental Energy Efficiency Patterns of African States

In other to assess the environmental energy efficiency in African States study employed both the traditional Data Envelopment Analysis (DEA) and the innovative Multi-Directional Efficiency Analysis (MEA) methodologies to evaluate environmental energy efficiency in African states. This comprehensive methodology allowed us to capture a more nuanced understanding of efficiency patterns, crucial for sustainable development initiatives. DEA, a widely-used technique, provided initial efficiency scores, while MEA, a novel approach, offered a more sophisticated analysis by accounting for both radial and non-radial inefficiencies. MEA's unique ability to capture inefficiencies from multiple directions allowed for a more robust evaluation of environmental energy efficiency. The findings, detailed in Tables 8 to 12, presented a wealth of efficiency metrics, including DEA efficiency scores, MEA's Ideal Reference Points (IRP), Potential Improvement Points (PIPs), inefficiency, efficiency, and overall efficiency scores across various variables. The comparison between DEA and MEA underscored MEA's superiority in capturing inefficiencies comprehensively. While DEA tended to yield higher efficiency scores, MEA's multi-directional approach provided a more accurate assessment, reflecting both radial and non-radial inefficiencies.

Environmental energy efficiency emerged as a critical concern for sustainable development in African states. The incorporation of MEA offered a holistic perspective, aligning with the region's need for nuanced insights into efficiency patterns. MEA's ability to capture both radial and non-radial inefficiencies holds significant implications for policymakers. By providing detailed insights, MEA equips decision-makers with the necessary tools to formulate effective policies for sustainable development. Additionally, our study offered variable-specific MEA efficiency scores for the sample countries from 2000 to 2019. This longitudinal analysis provided further insights into efficiency trends over time, facilitating informed decision-making.

Table 8: Capital service DEA and MEA scores

Countries	Capital services	DEA Efficiency (oev1.eff)	Ideal reference point (IRPx1xa)	Potential Improvement point (PIPx1xa)	MEA inefficiency (xa)	MEA efficiency (efx1xa)	Overall MEA Efficiency (ovse1m)
Angola	13642.12	1	13642.12	13642.12	0	1	1
Benin	887.2405	0.671595	516.126	747.2615	0.157769	0.842231	0.629567
Botswana	1850.156	0.982541	1336.47	1678.927	0.092548	0.907452	0.944538
Burkina Faso	871.8946	0.800836	648.3906	790.5418	0.093306	0.906694	0.763546
Burundi	193.3141	0.803403	122.3285	167.6683	0.132664	0.867336	0.761389
Cabo Verde	191.9693	0.676795	84.27132	151.0761	0.21302	0.78698	0.657314
Cameroon	2486.112	0.83771	1607.344	2145.799	0.136886	0.863114	0.802544
Central African Republic	324.595	1	324.5951	324.595	0	1	1
Chad	477.6592	0.889049	414.4078	451.4067	0.054961	0.945039	0.834653
Côte d'Ivoire	2559.19	1	2559.19	2559.19	0	1	1
Djibouti	113.2305	0.948472	102.7235	110.8969	0.020609	0.979391	0.938584
Egypt	18320.14	1	18320.14	18320.14	0	1	1
Eswatini	329.7085	1	329.7085	329.7085	0	1	1
Gabon	1279.221	1	1279.221	1279.221	0	1	1
Guinea	573.3508	0.901222	498.4572	550.1927	0.040391	0.959609	0.879393
Kenya	5372.316	1	5372.316	5372.316	0	1	1
Lesotho	277.1008	0.715829	112.4367	222.673	0.196419	0.803581	0.702361
Mauritania	976.59	0.725316	346.47	770.3259	0.211209	0.788792	0.713374
Mauritius	970.1594	1	970.1594	970.1594	0	1	1
Morocco	15392.91	0.885106	4298.334	11685.82	0.240831	0.759169	0.814248
Mozambique	1225.147	0.504705	529.9514	929.6604	0.241185	0.758815	0.481018
Niger	1311.49	0.625713	427.7117	887.6342	0.323186	0.676814	0.628598
Nigeria	30957.93	1	30957.93	30957.93	0	1	1
Rwanda	502.3325	1	502.3325	502.3325	0	1	1
Sao Tome and Principe	37.3574	1	37.3574	37.3574	0	1	1
Sierra Leone	167.1296	1	167.1296	167.1296	0	1	1
South Africa	28973.59	0.833144	10975.98	19974.79	0.310586	0.689414	0.674861
Sudan	3153.801	1	3153.801	3153.801	0	1	1
Togo	485.0028	0.649278	214.4584	391.1754	0.193458	0.806542	0.62552
Tunisia	3549.378	1	3549.378	3549.378	0	1	1
U.R. of Tanzania: Mainland	3910.371	1	3910.371	3910.371	0	1	1
Zimbabwe	707.2451	0.939113	664.1828	685.7139	0.030444	0.969556	0.768743

Table 9: Labour DEA and MEA scores

Countries	Labour	DEA Efficiency (oev1.eff)	Ideal reference point (IRPx1xb)	Potential Improvement point (PIPx1xb)	MEA inefficiency (xb)	MEA efficiency (efx1xb)	Overall MEA Efficiency (ovse1m)
Angola	16.07833	1	16.07833	16.07833	0	1	1
Benin	4.15568	0.671595	0.784405	2.884084	0.30599	0.69401	0.629567
Botswana	0.913966	0.982541	0.856558	0.89483	0.020938	0.979063	0.944538
Burkina Faso	6.75672	0.800836	2.405733	5.173012	0.23439	0.76561	0.763546
Burundi	4.841068	0.803403	1.197875	3.524849	0.271886	0.728114	0.761389
Cabo Verde	0.208237	0.676795	0.117658	0.173844	0.165163	0.834837	0.657314
Cameroon	10.07321	0.83771	4.802897	8.03222	0.202616	0.797384	0.802544
Central African Republic	1.80255	1	1.80255	1.80255	0	1	1
Chad	5.766202	0.889049	3.732976	4.922312	0.146351	0.853649	0.834653
Côte d'Ivoire	7.286382	1	7.286382	7.286382	0	1	1
Djibouti	0.364982	0.948472	0.266532	0.343117	0.059908	0.940092	0.938584
Egypt	25.9848	1	25.9848	25.9848	0	1	1
Eswatini	0.305422	1	0.305422	0.305422	0	1	1
Gabon	0.641878	1	0.641878	0.641878	0	1	1
Guinea	4.515535	0.901222	2.979954	4.040713	0.105153	0.894847	0.879393
Kenya	24.2133	1	24.2133	24.2133	0	1	1
Lesotho	0.654093	0.715829	0.185657	0.499257	0.236719	0.763281	0.702361
Mauritania	1.095617	0.725316	0.44797	0.883616	0.1935	0.8065	0.713374
Mauritius	0.57499	1	0.57499	0.57499	0	1	1
Morocco	11.37258	0.885106	7.113061	9.949325	0.125148	0.874852	0.814248
Mozambique	10.66711	0.504705	0.752582	6.453029	0.395054	0.604946	0.481018
Niger	8.532649	0.625713	2.858268	5.811243	0.31894	0.68106	0.628598
Nigeria	71.11517	1	71.11517	71.11517	0	1	1
Rwanda	5.161523	1	5.161523	5.161523	0	1	1
Sao Tome and Principe	0.063446	1	0.063446	0.063446	0	1	1
Sierra Leone	2.472388	1	2.472388	2.472388	0	1	1
South Africa	18.68636	0.833144	15.56842	17.12739	0.083428	0.916572	0.674861
Sudan	10.02483	1	10.02483	10.02483	0	1	1
Togo	3.081904	0.649278	0.646654	2.237335	0.274041	0.725959	0.62552
Tunisia	3.645834	1	3.645834	3.645834	0	1	1
U.R. of Tanzania: Mainland	22.91124	1	22.91124	22.91124	0	1	1
Zimbabwe	6.714952	0.939113	1.541924	4.128438	0.385187	0.614813	0.768743

Table 10: Energy Use DEA and MEA scores

Countries	Energy	DEA	Ideal	Potential	MEA	MEA	Overall

	Used	Efficiency (oev1.eff)	reference point (IRP1xc)	Improvement point (PIP1xc)	inefficiency (xc)	efficiency (efx1xc)	MEA Efficiency (ovse1m)
Angola	0.338	1	0.338	0.338	0	1	1
Benin	0.112	0.671595	0.046363	0.087243	0.221047	0.778953	0.629567
Botswana	0.079	0.982541	0.07709	0.078363	0.00806	0.99194	0.944538
Burkina Faso	0.065	0.800836	0.040261	0.055995	0.138532	0.861468	0.763546
Burundi	0.011	0.803403	0.007369	0.009688	0.11924	0.88076	0.761389
Cabo Verde	0.015	0.676795	0.007078	0.011992	0.200532	0.799468	0.657314
Cameroon	0.161	0.83771	0.126891	0.147791	0.082043	0.917957	0.802544
Central African Republic	0.005	1	0.005	0.005	0	1	1
Chad	0.024	0.889049	0.017277	0.021209	0.116274	0.883726	0.834653
Côte d’Ivoire	0.195	1	0.195	0.195	0	1	1
Djibouti	0.01	0.948472	0.007565	0.009459	0.05407	0.94593	0.938584
Egypt	4.031	1	4.031	4.031	0	1	1
Eswatini	0.023	1	0.023	0.023	0	1	1
Gabon	0.06	1	0.06	0.06	0	1	1
Guinea	0.048	0.901222	0.034656	0.043874	0.085958	0.914042	0.879393
Kenya	0.352	1	0.352	0.352	0	1	1
Lesotho	0.016	0.715829	0.008817	0.013626	0.148397	0.851603	0.702361
Mauritania	0.059	0.725316	0.036952	0.051783	0.122327	0.877673	0.713374
Mauritius	0.097	1	0.097	0.097	0	1	1
Morocco	0.855	0.885106	0.713927	0.807863	0.055131	0.944869	0.814248
Mozambique	0.245	0.504705	0.036081	0.156201	0.362446	0.637554	0.481018
Niger	0.034	0.625713	0.018466	0.02655	0.219122	0.780878	0.628598
Nigeria	1.655	1	1.655	1.655	0	1	1
Rwanda	0.019	1	0.019	0.019	0	1	1
Sao Tome and Principe	0.002	1	0.002	0.002	0	1	1
Sierra Leone	0.015	1	0.015	0.015	0	1	1
South Africa	5.492	0.833144	2.298027	3.895013	0.290784	0.709216	0.674861
Sudan	0.366	1	0.366	0.366	0	1	1
Togo	0.034	0.649278	0.012638	0.026591	0.217899	0.782101	0.62552
Tunisia	0.416	1	0.416	0.416	0	1	1
U.R. of Tanzania: Mainland	0.192	1	0.192	0.192	0	1	1
Zimbabwe	0.162	0.939113	0.106561	0.134281	0.171107	0.828893	0.768743

Table 11: GDP DEA and MEA scores

Countries	GDP	DEA Efficiency (oev1.eff)	Ideal reference point (IRP1ya)	Potential Improvement point (PIP1ya)	MEA inefficiency (ya)	MEA efficiency (efx1ya)	Overall MEA Efficiency

							(ovse1m)
Angola	225540	1	225540	225540	NA	1	1
Benin	36617.88	1.499	54895.9	43512.08	5.311401	0.841557	0.629567
Botswana	37341.26	1.013	37812.99	37498.5	237.4746	0.995807	0.944538
Burkina Faso	39322.71	1.21	47578.45	42327.71	13.0858	0.929007	0.763546
Burundi	9089.612	1.289	11713.08	10037.42	9.590106	0.905572	0.761389
Cabo Verde	3871.192	1.532	5931.687	4653.568	4.948	0.831876	0.657314
Cameroon	90019.03	1.167	105079.1	95851.22	15.43486	0.939154	0.802544
Central African Republic	4426.902	1	4426.902	4426.902	NA	1	1
Chad	24261.21	1.1	26692.26	25270.22	24.04467	0.960071	0.834653
Côte d'Ivoire	118822.5	1	118822.5	118822.5	NA	1	1
Djibouti	4436.217	1.063	4713.6	4497.823	72.00968	0.986303	0.938584
Egypt	1219797	1	1219797	1219797	NA	1	1
Eswatini	9557.596	1	9557.596	9557.596	NA	1	1
Gabon	30885.04	1	30885.04	30885.04	NA	1	1
Guinea	31043.89	1.093	33922.4	31933.96	34.87791	0.972128	0.879393
Kenya	215975.4	1	215975.4	215975.4	NA	1	1
Lesotho	6315.904	1.427	9013.708	7207.632	7.08277	0.87628	0.702361
Mauritania	21582.33	1.385	29895.31	24303.51	7.931235	0.888033	0.713374
Mauritius	29215.56	1	29215.56	29215.56	NA	1	1
Morocco	280390.1	1.125	315300.5	292054.9	24.03728	0.96006	0.814248
Mozambique	37536.65	1.855	69621.15	51173.89	2.752512	0.733512	0.481018
Niger	26082.36	1.34	34943.79	30332.26	6.137175	0.859889	0.628598
Nigeria	984634.9	1	984634.9	984634.9	NA	1	1
Rwanda	26900.52	1	26900.52	26900.52	NA	1	1
Sao Tome and Principe	866.8581	1	866.8581	866.8581	NA	1	1
Sierra Leone	13425.07	1	13425.07	13425.07	NA	1	1
South Africa	731735.1	1.2	877826.7	804780.9	10.01748	0.909235	0.674861
Sudan	180168.6	1	180168.6	180168.6	NA	1	1
Togo	16570.34	1.556	25785.63	19766.29	5.18478	0.838313	0.62552
Tunisia	128062.2	1	128062.2	128062.2	NA	1	1
U.R. of Tanzania: Mainland	130690.1	1	130690.1	130690.1	NA	1	1
Zimbabwe	46457.1	1.062	49318.84	47887.97	32.46776	0.970121	0.768743

Table 12: CO_2 Emission DEA and MEA scores

Countries	CO2 emissions	DEA Efficiency (oev1.eff)	Ideal reference point (IRP1yb)	Potential Improvement point (PIP1yb)	MEA inefficiency (yb)	MEA efficiency (efx1yb)	Overall MEA Efficiency (ovse1m)
Angola	23960	1	23960	23960	0	1	1
Benin	7420	0.671595	1069.836	5024.811	0.322802	0.677198	0.629567
Botswana	7310	0.982541	5459.281	6693.094	0.084392	0.915608	0.944538
Burkina Faso	4670	0.800836	1511.349	3520.288	0.246191	0.753809	0.763546
Burundi	690	0.803403	474.0284	611.9734	0.113082	0.886918	0.761389
Cabo Verde	610	0.676795	191.2551	451.0014	0.260653	0.739347	0.657314
Cameroon	9590	0.83771	5620.416	8052.732	0.160299	0.839701	0.802544
Central African Republic	230	1	230	230	0	1	1
Chad	2190	0.889049	1108.574	1741.154	0.204952	0.795048	0.834653
Côte d'Ivoire	10190	1	10190	10190	0	1	1
Djibouti	400	0.948472	293.8451	376.4234	0.058942	0.941058	0.938584
Egypt	247910	1	247910	247910	0	1	1
Eswatini	910	1	910	910	0	1	1
Gabon	5120	1	5120	5120	0	1	1

Guinea	3750	0.901222	1930.003	3187.233	0.150071	0.849929	0.879393
Kenya	17490	1	17490	17490	0	1	1
Lesotho	730	0.715829	260.9932	574.9752	0.212363	0.787637	0.702361
Mauritania	3690	0.725316	762.6284	2731.751	0.259688	0.740312	0.713374
Mauritius	4130	1	4130	4130	0	1	1
Morocco	64960	0.885106	28721.56	52851.45	0.1864	0.8136	0.814248
Mozambique	6950	0.504705	765.6002	4321.375	0.378219	0.621781	0.481018
Niger	1950	0.625713	1077.199	1531.409	0.214662	0.785338	0.628598
Nigeria	109890	1	109890	109890	0	1	1
Rwanda	1290	1	1290	1290	0	1	1
Sao Tome and Principe	140	1	140	140	0	1	1
Sierra Leone	860	1	860	860	0	1	1
South Africa	434350	0.833144	133532.6	283941.3	0.346285	0.653715	0.674861
Sudan	20860	1	20860	20860	0	1	1
Togo	12000	0.649278	583.7375	8040.727	0.329939	0.670061	0.62552
Tunisia	2310	1	2310	2310	0	1	1
U.R. of Tanzania: Mainland	29890	1	29890	29890	0	1	1
Zimbabwe	12380	0.939113	6348.946	9364.473	0.243581	0.75642	0.768743

Table 13 shows capital service variable specific efficiency. Most countries in Table 12 exhibited high efficiency in capital service in both 2018 and 2019. Notably, Angola, Central African Republic, Côte d'Ivoire, Egypt, Gabon, Kenya, Nigeria, Rwanda, Sao Tome and Principe, Tunisia, and U.R. of Tanzania: Mainland achieved perfect efficiency scores (1) in both years. Countries like Benin, Botswana, Cameroon, Chad, Djibouti, Eswatini, Mauritius, Sierra Leone, and Zimbabwe consistently demonstrated strong efficiency.

Table 14 shows labour variable specific efficiency scores. The efficiency varies across countries, with some achieving perfect scores (1) consistently (e.g., Central African Republic, Côte d'Ivoire, Egypt, Gabon, Kenya, Nigeria, Rwanda, Sao Tome and Principe, Tunisia) while others exhibit fluctuations. Overall, there's room for improvement in labour efficiency across several countries, with some experiencing improvements from 2018 to 2019 (e.g., Djibouti, Eswatini, Gabon, Mauritania).

Table 15 shows Efficiency in energy usage is generally high, with several countries consistently scoring close to perfect efficiency (1). Notable examples include Angola, Central African

Republic, Côte d'Ivoire, Egypt, Eswatini, Kenya, Nigeria, Rwanda, Sao Tome and Principe, Tunisia. However, there are fluctuations in efficiency scores among other countries, indicating potential areas for improvement (e.g., Benin, Burundi, Mozambique, South Africa).

Table 16 shows CO2 emission efficiency varies across countries, with some achieving perfect scores (1) consistently (e.g., Central African Republic, Côte d'Ivoire, Egypt, Gabon, Kenya, Nigeria, Rwanda, Sao Tome and Principe, Tunisia). However, some countries show fluctuations and potential inefficiencies, suggesting a need for targeted environmental policies (e.g., Burundi, Mozambique, South Africa, Zimbabwe).

Table 17 shows GDP efficiency is generally high across most countries, with many consistently achieving perfect scores (1). Notable examples include Central African Republic, Côte d'Ivoire, Egypt, Gabon, Kenya, Nigeria, Rwanda, Sao Tome and Principe, Tunisia. However, there are fluctuations in efficiency scores among other countries, indicating potential areas for improvement (e.g., Benin, Mozambique, Niger, Zimbabwe).

However, there are some infeasibilities (NA) of some variables. Estimating the efficiency of a particular period relative to another time period showed infeasibilities of certain variables.

The analysis indicates varying degrees of environmental energy efficiency across African states. While some countries consistently demonstrate high efficiency across different variables, others exhibit fluctuations and potential areas for improvement. Policymakers could use these findings to implement targeted interventions aimed at enhancing environmental energy efficiency, such as promoting renewable energy sources, improving labour productivity, and reducing CO2 emissions. Additionally, further research and analysis are needed to understand the specific factors driving efficiency patterns in each country and to develop tailored strategies for sustainable development.

Table 13: MEA Variable specific efficiency of capital service

Country	Efficiency 2018	Efficiency 2019	Efficiency 2018/2019	Efficiency 2019/2018
Angola	1	0.804831	NA	0.7836804
Benin	0.842231	0.833618	0.9584816	0.8288396
Botswana	0.907452	0.876117	0.9397521	NA
Burkina Faso	0.906694	0.869042	1.0356909	0.865543
Burundi	0.867336	0.833321	0.9027292	0.8442699
Cabo Verde	0.78698	0.784522	0.8297898	0.7863258
Cameroon	0.863114	0.870513	0.9453259	0.8752308
Central African Republic	1	1	NA	NA
Chad	0.945039	0.958302	1.0091657	0.934062
Côte d'Ivoire	1	1	NA	NA
Djibouti	0.979391	1	1.1119823	0.9701511
Egypt	1	1	NA	NA
Eswatini	1	1	0.9796036	NA
Gabon	1	1	1.010772	NA
Guinea	0.959609	0.943652	0.9613213	0.961937
Kenya	1	1	NA	NA
Lesotho	0.803581	0.781613	0.8748753	0.7836096
Mauritania	0.788792	0.792171	0.8142514	0.7961047
Mauritius	1	1	1.0591483	NA
Morocco	0.759169	0.746285	0.8024638	0.7554624
Mozambique	0.758815	0.719844	0.9126289	0.7155997
Niger	0.676814	0.654212	0.6927781	0.680391
Nigeria	1	1	NA	NA
Rwanda	1	1	NA	NA
Sao Tome and Principe	1	1	NA	NA
Sierra Leone	1	1	0.9842081	NA
South Africa	0.689414	0.692377	0.7157777	0.6834235
Sudan	1	1	1.008043	NA
Togo	0.806542	0.809817	0.8569331	0.8071683
Tunisia	1	1	NA	NA
U.R. of Tanzania: Mainland	1	1	1.0265217	NA
Zimbabwe	0.969556	0.925255	0.9927544	0.9233055
Geomean	**0.909655**	**0.895909**	**0.925258**	**0.818595**

Table 14: MEA variable specific efficiency of labour

Country	Efficiency 2018	Efficiency 2019	Efficiency 2018r2019	Efficiency 2019r2018
Angola	1	0.968819	NA	0.9545358
Benin	0.69401	0.713214	0.713952	0.722185
Botswana	0.979063	0.950487	0.9405241	NA
Burkina Faso	0.76561	0.794658	0.8139611	0.7660737
Burundi	0.728114	0.702391	0.7348829	0.6968786
Cabo Verde	0.834837	0.840366	0.84699	0.8407142
Cameroon	0.797384	0.82677	0.8389721	0.8219201
Central African Republic	1	1	NA	NA
Chad	0.853649	0.872507	0.9035757	0.8454747
Côte d'Ivoire	1	1	NA	NA
Djibouti	0.940092	1	0.9882989	0.9712172
Egypt	1	1	NA	NA
Eswatini	1	1	1.0124269	NA
Gabon	1	1	1.014135	NA
Guinea	0.894847	0.867377	0.9068536	0.8835394
Kenya	1	1	NA	NA
Lesotho	0.763281	0.756074	0.7794988	0.7534498
Mauritania	0.8065	0.808654	0.8234674	0.8127269
Mauritius	1	1	1.0099482	NA
Morocco	0.874852	0.833034	0.8407455	0.8711634
Mozambique	0.604946	0.593796	0.6281235	0.5913632
Niger	0.68106	0.666021	0.6674735	0.6907793
Nigeria	1	1	NA	NA
Rwanda	1	1	NA	NA
Sao Tome and Principe	1	1	NA	NA
Sierra Leone	1	1	0.995373	NA
South Africa	0.916572	0.90847	0.9057251	0.9181862
Sudan	1	1	1.0185152	NA
Togo	0.725959	0.746097	0.74739	0.738638
Tunisia	1	1	NA	NA
U.R. of Tanzania: Mainland	1	1	0.8117327	NA
Zimbabwe	0.614813	0.567913	0.6810975	0.5966733
Geomean	**0.879516**	**0.876906**	**0.844632**	**0.784851**

Table 15: MEA variable specific efficiency of Energy use

Country	Efficiency 2018	Efficiency 2019	Efficiency 2018r2019	Efficiency 2019r2018
Angola	1	0.992637	NA	0.9603064
Benin	0.778953	0.817281	0.7110278	0.8195679
Botswana	0.99194	0.980116	0.9575941	NA
Burkina Faso	0.861468	0.862641	0.8647095	0.8639959
Burundi	0.88076	0.870621	1.0278501	0.8398692
Cabo Verde	0.799468	0.828418	0.8162822	0.8134311
Cameroon	0.917957	0.93384	0.9177683	0.9373261
Central African Republic	1	1	NA	NA
Chad	0.883726	0.920722	0.9585467	0.8767387
Côte d'Ivoire	1	1	NA	NA
Djibouti	0.94593	1	0.8980561	0.9849059
Egypt	1	1	NA	NA
Eswatini	1	1	0.9629421	NA
Gabon	1	1	0.95716	NA
Guinea	0.914042	0.913695	0.9779087	0.9104548
Kenya	1	1	NA	NA
Lesotho	0.851603	0.849738	0.9057821	0.837541
Mauritania	0.877673	0.874342	0.890057	0.8857309
Mauritius	1	1	1.0314453	NA
Morocco	0.944869	0.929278	0.9626713	0.9451745
Mozambique	0.637554	0.6276	0.6417001	0.6275242
Niger	0.780878	0.786741	0.8055554	0.7944472
Nigeria	1	1	NA	NA
Rwanda	1	1	NA	NA
Sao Tome and Principe	1	1	NA	NA
Sierra Leone	1	1	0.9167149	NA
South Africa	0.709216	0.692438	0.7113656	0.7040356
Sudan	1	1	0.943369	NA
Togo	0.782101	0.811641	0.7752924	0.8010492
Tunisia	1	1	NA	NA
U.R. of Tanzania: Mainland	1	1	0.9718231	NA
Zimbabwe	0.828893	0.691199	0.828683	0.7188764
Geomean	**0.912368**	**0.911455**	**0.882151**	**0.836948**

Table 16: MEA variable specific efficiency of CO2 Emission

Country	Efficiency 2018	Efficiency 2019	Efficiency 2018r2019	Efficiency 2019r2018
Angola	1	0.953531	NA	0.9396082
Benin	0.677198	0.693727	0.6693419	0.689021
Botswana	0.915608	0.898659	0.8563976	NA
Burkina Faso	0.753809	0.755348	0.8335429	0.7455779
Burundi	0.886918	0.869022	0.9166931	0.8596576
Cabo Verde	0.739347	0.745176	0.788001	0.7387416
Cameroon	0.839701	0.897638	0.8633194	0.8771355
Central African Republic	1	1	NA	NA
Chad	0.795048	0.826342	0.8547703	0.7878057
Côte d'Ivoire	1	1	NA	NA
Djibouti	0.941058	1	1.0099053	0.981627
Egypt	1	1	NA	NA
Eswatini	1	1	1.0331897	NA
Gabon	1	1	1.0057359	NA
Guinea	0.849929	0.859748	0.8841537	0.8571936
Kenya	1	1	NA	NA
Lesotho	0.787637	0.780073	0.8335369	0.7712573
Mauritania	0.740312	0.748341	0.7839753	0.7518919
Mauritius	1	1	1.0058423	NA
Morocco	0.8136	0.797675	0.869711	0.8112203
Mozambique	0.621781	0.610408	0.6733524	0.6063304
Niger	0.785338	0.752611	0.8007497	0.7803561
Nigeria	1	1	NA	NA
Rwanda	1	1	NA	NA
Sao Tome and Principe	1	1	NA	NA
Sierra Leone	1	1	1.0235099	NA
South Africa	0.653715	0.64432	0.6517843	0.6522804
Sudan	1	1	0.9887013	NA
Togo	0.670061	0.689574	0.7029585	0.6759705
Tunisia	1	1	NA	NA
U.R. of Tanzania: Mainland	1	1	0.7063119	NA
Zimbabwe	0.75642	0.664004	0.7227399	0.6882898
Geomean	**0.872158**	**0.87023**	**0.838161**	**0.771074**

Table 17: MEA variable specific efficiency of GDP

Country	Efficiency 2018	Efficiency 2019	Efficiency 2018r2019	Efficiency 2019r2018
Angola	1	0.994121	NA	0.9740374
Benin	0.841557	0.853432	0.8057744	0.8577284
Botswana	0.995807	0.989272	0.9599833	NA
Burkina Faso	0.929007	0.918256	0.9042809	0.9123118
Burundi	0.905572	0.880393	0.8977852	0.8781997
Cabo Verde	0.831876	0.83933	0.8072741	0.8425793
Cameroon	0.939154	0.948714	0.9206862	0.9522645
Central African Republic	1	1	NA	NA
Chad	0.960071	0.976152	0.9634873	0.9509758
Côte d'Ivoire	1	1	NA	NA
Djibouti	0.986303	1	0.9354623	0.9927851
Egypt	1	1	NA	NA
Eswatini	1	1	0.9895104	NA
Gabon	1	1	0.9708499	NA
Guinea	0.972128	0.966943	0.9330152	0.9742185
Kenya	1	1	NA	NA
Lesotho	0.87628	0.865827	0.8746715	0.8595389
Mauritania	0.888033	0.890591	0.8533931	0.8959426
Mauritius	1	1	0.972043	NA
Morocco	0.96006	0.944783	0.9255971	0.9597889
Mozambique	0.733512	0.670566	0.7275552	0.6681568
Niger	0.859889	0.845334	0.8143852	0.8676517
Nigeria	1	1	NA	NA
Rwanda	1	1	NA	NA
Sao Tome and Principe	1	1	NA	NA
Sierra Leone	1	1	0.959823	NA
South Africa	0.909235	0.899532	0.897009	0.9111482
Sudan	1	1	0.989926	NA
Togo	0.838313	0.862615	0.8176896	0.852764
Tunisia	1	1	NA	NA
U.R. of Tanzania: Mainland	1	1	0.9392356	NA
Zimbabwe	0.970121	0.925523	1.0207054	0.9201732
Geomean	**0.94727**	**0.942682**	**0.904833**	**0.894873**

Fig 3 shows the efficiency of capital service fluctuates over the years but generally shows an increasing trend from 2000 to 2008, followed by slight fluctuations. There is a dip in efficiency in 2009, followed by a gradual increase until 2012. From 2012 onwards, there are minor fluctuations with no clear trend. Overall, capital service efficiency remains relatively stable over the analyzed period, with some variation around the mean efficiency.

Labour efficiency shows a decreasing trend from 2000 to 2012, with minor fluctuations. There is a slight increase in efficiency from 2012 to 2013, followed by fluctuations with no clear trend. The efficiency of labour exhibits a downward trend towards the end of the analyzed period, reaching a lower level by 2019 compared to earlier years.

Energy usage efficiency shows minor fluctuations throughout the analyzed period without a clear trend. There is no discernible pattern of increase or decrease in efficiency over the years, indicating stability in energy usage efficiency.

GDP efficiency demonstrates a slight increasing trend from 2000 to 2016, with minor fluctuations. There is a slight decrease in efficiency from 2016 to 2017, followed by a slight increase in 2018 before a slight decrease again in 2019. Overall, GDP efficiency remains relatively stable with minor fluctuations around the mean efficiency.

CO2 emission efficiency shows a decreasing trend from 2000 to 2012, followed by fluctuations with no clear trend. There is a slight increase in efficiency from 2017 to 2018, followed by a slight decrease in 2019. Overall, CO2 emission efficiency exhibits variability over the analyzed period, with fluctuations around the mean efficiency.

Capital service and GDP efficiency generally show relatively stable trends with minor fluctuations, indicating consistent performance over the years. Labour efficiency demonstrates a decreasing trend, suggesting potential challenges in labour productivity and resource utilization. Energy usage efficiency remains relatively stable with no clear trend, indicating consistent performance in energy utilization. CO2 emission efficiency shows variability over the years, with periods of both increase and decrease, reflecting fluctuations in environmental sustainability efforts and policies. Overall, understanding these variable-specific efficiency trends can help policymakers identify areas of improvement and implement targeted strategies to enhance overall economic and environmental sustainability.

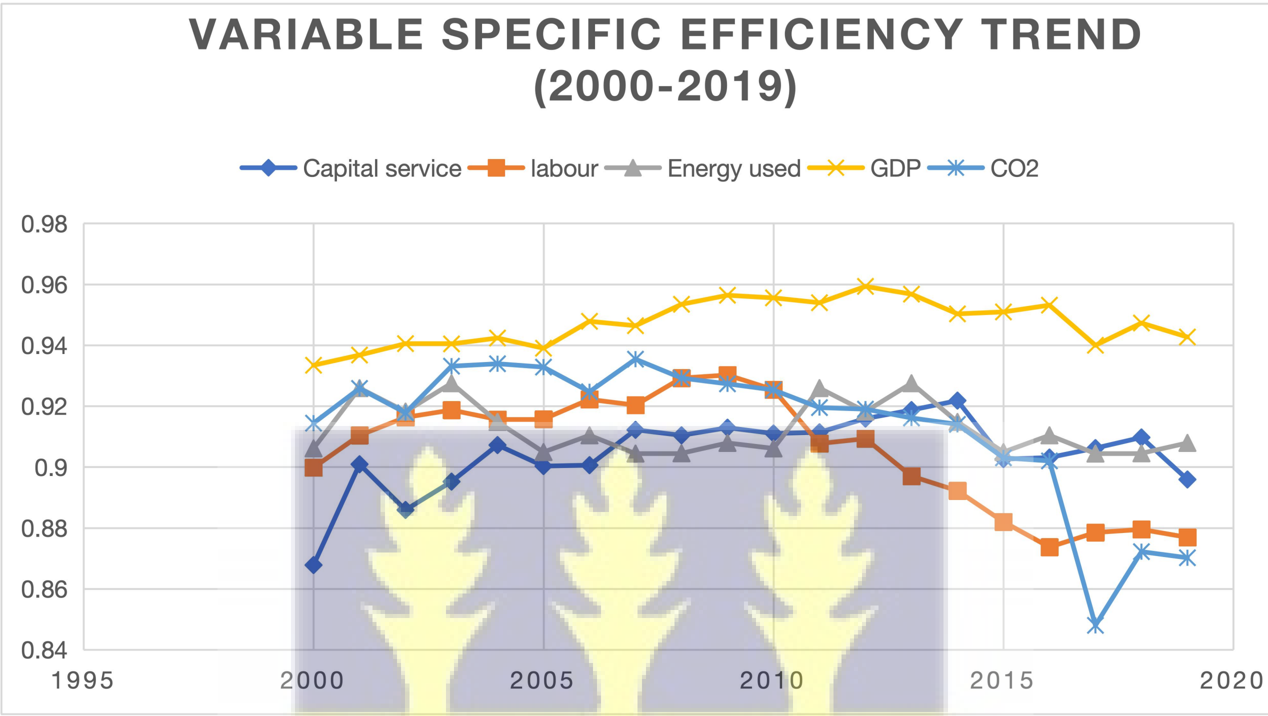

Figure 3: Variables Specific Efficiency Trend

4.4 Evaluate the environmental energy efficiency status of African states

To evaluate the environmental energy efficiency status of African states the study analyses Table 18, which presents the energy efficiency status of African states in 2018. The Table 18 provides efficiency scores for various aspects, including capital service, labour, energy use, GDP, and CO_2 emissions, for each African states. The efficiency scores range from 0.481 to 1, with a geometric mean of approximately 0.848. States with efficiency scores closer to 1 are considered more energy-efficient, while those closer to 0 are less efficient. For example, countries like Angola, Central African Republic, Côte d'Ivoire, Egypt, Eswatini, Gabon, Kenya, Mauritius, Nigeria, Rwanda, Sao Tome and Principe, Sierra Leone, Sudan, Tunisia, and U.R. of Tanzania: Mainland have perfect efficiency scores of 1 in all aspects evaluated. There are notable variations in efficiency scores among African states. Some countries, like Angola and Côte d'Ivoire, have perfect efficiency scores across all aspects, indicating a highly efficient use of resources. However, other countries, such as Mozambique and Togo, have lower efficiency scores, suggesting potential areas for improvement in resource utilization. The efficiency scores reflect the effectiveness of resource allocation and utilization within each country. Factors such as governance, infrastructure, technological advancement, and economic development likely influence energy efficiency levels. For instance, countries with stronger governance structures and more advanced infrastructure may exhibit higher efficiency scores. The findings underscore the importance of implementing policies and initiatives aimed at improving energy efficiency in African states. Governments and policymakers can use the efficiency scores as benchmarks to identify areas for improvement and prioritize resource allocation accordingly. Strategies may include investing in renewable energy sources, promoting energy-saving technologies, and enhancing infrastructure development. The geomean provides a summary measure of overall energy efficiency across all evaluated aspects. It serves as a useful reference point for comparing the average efficiency levels among African states.

The analysis of Table 18 highlights the varying energy efficiency statuses among African states and underscores the importance of continuous efforts to enhance resource efficiency and promote sustainable development across the region. By addressing inefficiencies and implementing targeted interventions, African countries can strive towards achieving higher levels of energy efficiency and contribute to long-term environmental sustainability.

Table 18: Energy efficiency status of African States 2018

Countries	Capital Service	Labour	Energy Used	GDP	CO2
Angola	1	1	1	1	1
Benin	0.629567	0.629567	0.629567	0.629567	0.629567
Botswana	0.944538	0.944538	0.944538	0.944538	0.944538
Burkina Faso	0.763546	0.763546	0.763546	0.763546	0.763546
Burundi	0.761389	0.761389	0.761389	0.761389	0.761389
Cabo Verde	0.657314	0.657314	0.657314	0.657314	0.657314
Cameroon	0.802544	0.802544	0.802544	0.802544	0.802544
Central African Republic	1	1	1	1	1
Chad	0.834653	0.834653	0.834653	0.834653	0.834653
Côte d'Ivoire	1	1	1	1	1
Djibouti	0.938584	0.938584	0.938584	0.938584	0.938584
Egypt	1	1	1	1	1
Eswatini	1	1	1	1	1
Gabon	1	1	1	1	1
Guinea	0.879393	0.879393	0.879393	0.879393	0.879393
Kenya	1	1	1	1	1
Lesotho	0.702361	0.702361	0.702361	0.702361	0.702361
Mauritania	0.713374	0.713374	0.713374	0.713374	0.713374
Mauritius	1	1	1	1	1
Morocco	0.814248	0.814248	0.814248	0.814248	0.814248
Mozambique	0.481018	0.481018	0.481018	0.481018	0.481018
Niger	0.628598	0.628598	0.628598	0.628598	0.628598
Nigeria	1	1	1	1	1
Rwanda	1	1	1	1	1
Sao Tome and Principe	1	1	1	1	1
Sierra Leone	1	1	1	1	1
South Africa	0.674861	0.674861	0.674861	0.674861	0.674861
Sudan	1	1	1	1	1
Togo	0.62552	0.62552	0.62552	0.62552	0.62552
Tunisia	1	1	1	1	1
U.R. of Tanzania: Mainland	1	1	1	1	1
Zimbabwe	0.768743	0.768743	0.768743	0.768743	0.768743
Geomean	**0.84756353**	**0.8475635**	**0.8475635**	**0.8475635**	**0.84756353**

4.5 Energy consumption slacks and the energy savings potential of African states.

To investigate the energy consumption slacks, and the energy savings potential of African states the study estimated the variable specific efficiency of energy use. The tables below show the efficiency score of energy use. Table 19 shows energy consumption efficiency trend from 2000 to 2009. The table 19 shows that many countries exhibit stable or consistently high energy consumption efficiency scores throughout the period. For instance, Angola, Botswana, Burundi, Chad, Djibouti, Egypt, Guinea, Kenya, Rwanda, Sao Tome and Principe, Sierra Leone, Sudan, and Nigeria consistently scored 1, indicating high energy consumption efficiency. However, some countries show fluctuating efficiency scores, such as Benin, Cabo Verde, Central African Republic, Lesotho, Mauritania, Morocco, Mozambique, Niger, Togo, and Zimbabwe. Countries with fluctuating efficiency scores may have potential areas for improvement in energy management practices, infrastructure development, or policy implementation to enhance efficiency and sustainability.

The table 20 shows energy consumption trend from 2010 to 2019, Similar to the previous period, many countries maintain high or stable energy consumption efficiency scores. Countries like Angola, Botswana, Burundi, Chad, Djibouti, Egypt, Gabon, Guinea, Kenya, Mauritius, Nigeria, Rwanda, Sao Tome and Principe, Sudan, and Tunisia sustain or improve their efficiency scores. Some countries, including Benin, Burundi, Central African Republic, Lesotho, Morocco, Mozambique, Niger, Togo, and Zimbabwe, continue to exhibit fluctuating efficiency scores. The improvement in efficiency scores for certain countries suggests successful interventions, policies, or investments in energy infrastructure and management. Countries with fluctuating scores may benefit from targeted initiatives to address underlying factors affecting energy consumption efficiency. The average efficiency scores for the majority of countries remain high across both periods, indicating overall improvements or stability in energy consumption efficiency over the two decades. This trend reflects a global focus on energy efficiency initiatives and sustainable development goals during the period under review.

While some countries consistently maintain high efficiency scores, others struggle to improve or sustain efficiency levels. Regional disparities in infrastructure, technology adoption, economic development, and policy frameworks may contribute to variations in energy consumption efficiency among countries. Policymakers can learn from countries with sustained or improved efficiency scores and replicate successful strategies to promote energy efficiency and sustainable development. Targeted interventions and capacity-building efforts may be required to support countries experiencing fluctuating efficiency scores and address underlying challenges. Analysis of efficiency scores provides insights into the potential for energy savings and opportunities for optimization in energy consumption across different sectors and regions. Identifying and addressing inefficiencies can contribute to energy security, environmental sustainability, and economic growth in African states.

The analysis of energy consumption efficiency scores highlights both progress and challenges in energy management across African countries. Continued efforts to promote energy efficiency, coupled with targeted interventions and international collaboration, are essential for achieving sustainable development goals and addressing global energy challenges.

Table 19: Variables specific efficiency scores of the 32 countries from 2000-2009 for energy Used

Country	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**
Angola	1	1	1	1	1	1	1	1	1	0.892731
Benin	0.850985	0.853531	0.863061	0.811586	0.777752	0.759909	0.764258	0.763514	0.774853	0.72445
Botswana	1	1	1	1	1	1	1	1	1	1
Burkina Faso	0.965922	1	1	1	1	1	1	0.957364	0.990131	0.979136
Burundi	1	1	1	1	1	1	1	1	1	1
Cabo Verde	1	1	1	1	1	0.86861	0.888758	0.871912	0.921528	0.884231
Cameroon	0.901965	1	1	1	1	1	1	0.933423	0.951521	0.904609
Central African Republic	1	1	1	0.952808	1	0.800819	0.855718	0.839736	0.803792	0.822186
Chad	1	1	1	1	1	1	1	1	1	1
Côte d’Ivoire	0.816482	0.814218	0.828642	0.846276	0.845122	0.824667	0.894401	0.898434	0.933682	1
Djibouti	1	1	1	1	1	1	1	1	1	1
Egypt	1	1	1	1	1	1	1	1	1	1
Eswatini	0.816841	0.826287	0.838327	0.888021	1	1	1	1	1	1
Gabon	1	1	1	1	1	1	1	1	1	1
Guinea	1	1	1	1	1	1	1	1	1	1
Kenya	1	1	1	1	1	1	1	1	1	1
Lesotho	0.784043	0.792965	0.799521	0.806642	0.806377	0.76632	0.777039	0.745856	0.831551	0.786426
Mauritania	1	1	1	1	1	1	1	1	1	0.95465
Mauritius	1	1	1	1	1	1	0.898138	0.892252	0.919606	1
Morocco	0.860501	0.877128	0.875716	0.879596	0.869669	0.835345	0.849538	0.82262	0.8162	0.815568
Mozambique	0.639758	0.63691	0.648578	0.645592	0.648815	0.669161	0.678169	0.702615	0.728574	1
Niger	0.910959	1	0.94538	0.909144	0.613013	0.648862	0.879356	0.626559	0.68414	0.609448
Nigeria	1	1	1	1	1	1	1	1	1	1
Rwanda	1	1	1	1	1	1	1	1	1	1
Sao Tome and Principe	1	1	1	1	1	1	1	1	1	1
Sierra Leone	0.842975	0.848998	0.970583	0.993484	0.872642	0.974495	1	1	1	1
South Africa	0.669812	1	0.683483	1	1	1	0.716938	1	0.710613	0.710514
Sudan	1	1	1	1	1	1	1	1	1	1
Togo	0.73871	0.755074	0.739937	0.707485	0.670722	0.664578	0.696226	0.67065	0.665405	0.625555
Tunisia	0.863831	0.851898	0.850445	0.887944	0.917402	0.904103	0.942269	0.993838	0.955741	1
U.R. of Tanzania: Mainland	1	1	1	1	1	1	1	1	1	1
Zimbabwe	0.608099	0.612701	0.606209	0.595883	0.588336	0.57528	0.573755	0.557408	0.566528	0.658067
GEO MEAN	0.9061	0.9259	0.9182	0.9275	0.9148	0.9049	0.9104	0.9044	0.9045	0.9079

Table 20: Variables specific efficiency scores of the 32 countries from 2010-2019 for energy Used

Country	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Average
Angola	0.979523	1	1	1	1	0.986213	0.997184	1	1	0.992637	0.992
Benin	0.694187	0.718211	0.750456	0.790526	0.809752	0.805233	0.796715	0.807365	0.778953	0.817281	0.786
Botswana	1	1	1	1	1	1	0.965453	0.976627	0.99194	0.980116	0.996
Burkina Faso	0.929315	1	0.809925	0.87951	0.872341	0.778719	0.863744	0.883526	0.861468	0.862641	0.932
Burundi	1	0.820517	0.791899	0.801943	1	0.809966	0.787301	1	0.88076	0.870621	0.938
Cabo Verde	0.876731	0.821997	0.846767	0.848045	0.820963	0.818277	0.807803	0.810548	0.799468	0.828418	0.886
Cameroon	0.857432	0.857759	0.84789	1	0.888674	0.89922	0.930648	0.91511	0.917957	0.93384	0.937
Central African Republic	0.811168	0.688666	0.687466	0.677761	0.676481	0.673633	0.680807	0.80903	1	1	0.839
Chad	1	1	1	1	1	1	1	1	0.883726	0.920722	0.990
Côte d'Ivoire	0.961494	1	1	1	1	1	1	1	1	1	0.933
Djibouti	1	1	1	1	1	1	0.966745	0.954281	0.94593	1	0.993
Egypt	1	1	1	1	1	1	1	1	1	1	1.000
Eswatini	1	1	1	0.990378	1	1	1	1	1	1	0.968
Gabon	1	1	1	1	1	1	1	1	1	1	1.000
Guinea	1	1	1	1	1	1	0.816235	0.866796	0.914042	0.913695	0.976
Kenya	1	1	1	1	1	1	1	1	1	1	1.000
Lesotho	0.797292	0.84346	0.841424	0.858239	0.856993	0.854605	0.869194	0.812722	0.851603	0.849738	0.817
Mauritania	1	1	0.976229	1	0.978822	0.987122	1	0.913233	0.877673	0.874342	0.978
Mauritius	1	1	1	1	1	1	1	1	1	1	0.985
Morocco	0.819281	0.848908	0.851975	0.878509	0.893062	0.902387	0.929202	0.947666	0.944869	0.929278	0.872
Mozambique	1	0.691709	0.639489	0.610904	0.547379	0.561857	0.581041	0.620146	0.637554	0.6276	0.676
Niger	0.574002	0.548823	0.576577	0.595089	0.614436	0.601234	0.592728	0.740961	0.780878	0.786741	0.712
Nigeria	1	1	1	1	1	1	1	1	1	1	1.000
Rwanda	1	1	1	1	1	1	1	1	1	1	1.000
Sao Tome and Principe	1	1	1	1	1	1	1	1	1	1	1.000
Sierra Leone	1	0.933129	0.98603	1	1	1	1	1	1	1	0.971
South Africa	0.711832	0.722893	0.731303	0.729721	1	0.716346	0.711018	0.709883	0.709216	0.692438	0.796
Sudan	1	1	1	1	1	1	1	1	1	1	1.000
Togo	0.630053	0.644709	0.660404	0.666456	0.663008	0.66495	0.712097	0.750117	0.782101	0.811641	0.696
Tunisia	1	1	1	1	0.995279	0.970027	0.970965	0.962146	1	1	0.953
U.R. of Tanzania: Mainland	1	1	1	0.992988	0.967529	0.978794	0.955525	1	1	1	0.995
Zimbabwe	0.649809	0.654235	0.714401	0.68425	0.657856	0.677511	0.745237	0.812596	0.828893	0.691199	0.653
GEO MEAN	0.9046	0.8877	0.8861	0.8950	0.9020	0.8843	0.8856	0.9086	0.9124	0.9115	

The fig 4 shows energy consumption fluctuates over the years, showing a slight increase from 2000 to 2003, followed by a decrease until 2005, a slight rise until 2008, and then a relatively stable pattern until 2019. The overall trend suggests fluctuations in energy usage, indicating potential inefficiencies or variations in energy management practices across African states during the period under review. Years with higher energy consumption, such as 2003 and 2018, may indicate periods of increased energy demand or less efficient energy utilization. Conversely, years with lower energy consumption, such as 2005 and 2011, may suggest improvements in energy efficiency, adoption of renewable energy sources, or economic factors influencing energy demand.

Analysis of the Fig 3 can help identify opportunities for energy savings by examining years with lower energy consumption relative to the overall trend. For instance, policymakers can focus on understanding the factors contributing to reduced energy consumption in years like 2005, 2011, and 2015 to replicate successful strategies and promote energy efficiency measures. The fluctuating nature of energy consumption underscores the importance of implementing robust energy policies, investing in energy-efficient technologies, and promoting renewable energy sources to mitigate energy consumption slacks and enhance energy savings potential. Addressing energy consumption slacks can contribute to energy security, environmental sustainability, and economic development in African states.

The analysis of energy consumption trends highlights fluctuations in energy usage over the years and underscores the importance of investigating energy consumption slacks to identify opportunities for energy savings and promote sustainable energy practices in African states.

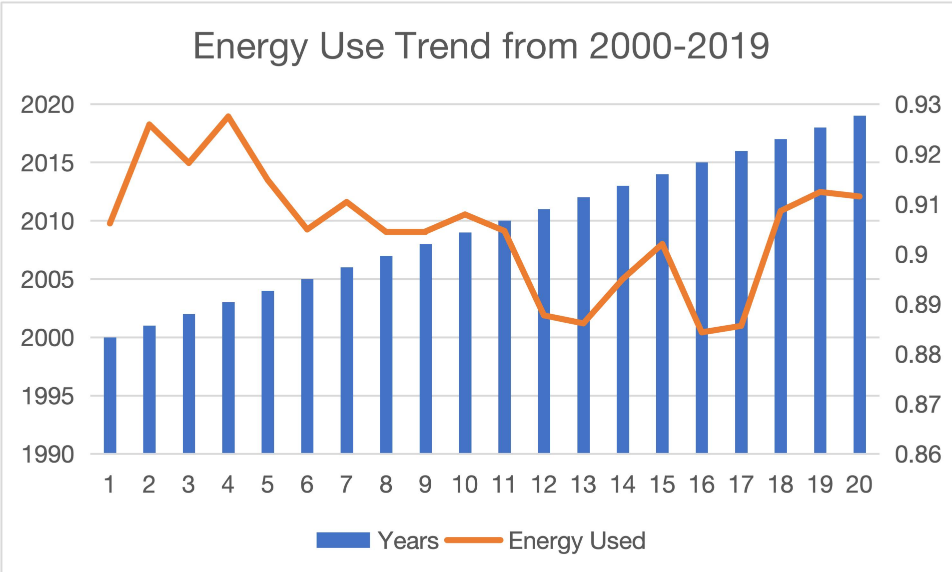

Figure 4: Energy Use Trend

4.6 Statistically compare the differences in the variable specific efficiencies of African regional blocs.

To statistically compare the difference in the variable's specific efficiencies of African regional blocs, the study employed summary statistic of each variable across the regional blocs and ANOVA which will help determine whether there are statistically significant differences in means among the five groups.

The Table 21 presents variable specific efficiencies of African countries within different regional blocs, namely AMU, EAC, ECCAS, ECOWAS, and SADC. Each regional bloc demonstrates variations in the efficiency of utilizing capital service, labour, energy, GDP generation, and CO2 emissions.

Significant differences exist in the efficiency levels among countries within the same regional bloc. For example: In the AMU bloc, Egypt and Tunisia exhibit higher efficiencies across all variables compared to Morocco, Mauritania, and Sudan. Within the EAC bloc, Kenya demonstrates higher efficiencies in labour, energy use, and GDP generation compared to Djibouti and Burundi. In the ECCAS bloc, countries like Chad and Cameroon show varying levels of efficiency across different variables compared to Angola and Central African Republic. Similar disparities can be observed in the ECOWAS and SADC blocs.

The geometric mean provides an overall measure of efficiency across all regional blocs. In 2018, the geometric mean efficiencies were highest for capital service (0.9097) and GDP generation (0.9473), indicating relatively better performance in these areas compared to labor (0.8795), energy use (0.9124), and CO2 emissions (0.8722). Understanding efficiency variations among countries within regional blocs can inform policy interventions aimed at improving resource allocation, enhancing productivity, and promoting sustainable development. Policymakers may focus on identifying and addressing inefficiencies, promoting knowledge sharing and best practices, and fostering collaboration among member states to achieve common goals.

Disparities in variable specific efficiencies highlight both challenges and opportunities for intra-bloc cooperation and integration. Addressing inefficiencies in resource utilization, promoting technological innovation, and fostering regional cooperation can unlock significant economic and social development potential within African regional blocs. The analysis of variable specific efficiencies across African regional blocs provides valuable insights into the disparities and opportunities for enhancing economic performance, resource utilization, and sustainable development within these blocs. Policymakers can leverage these insights to formulate targeted interventions and foster collaboration to address efficiency gaps and promote inclusive growth across the continent.

Table 21: 2018 Variable specific efficiencies of African regional blocs.

Group	Country	capital service	Labour	Energy Used	GDP	CO2
AMU	Egypt	1	1	1	1	1
AMU	Mauritania	0.788792	1	0.877673	1	1
AMU	Morocco	0.759169	0.8065	0.944869	0.888033	0.740312
AMU	Sudan	1	0.874852	1	0.96006	0.8136
AMU	Tunisia	1	1	1	1	1
EAC	Burundi	0.867336	1	0.88076	1	1
EAC	Djibouti	0.979391	0.728114	0.94593	0.905572	0.886918
EAC	Kenya	1	0.940092	1	0.986303	0.941058
EAC	Rwanda	1	1	1	1	1
EAC	U.R. of Tanzania: Mainland	1	1	1	1	1
ECCAS	Angola	1	1	1	1	1
ECCAS	Cameroon	0.863114	0.797384	0.917957	0.939154	0.839701
ECCAS	Central African Republic	1	1	1	1	1
ECCAS	Chad	0.945039	0.853649	0.883726	0.960071	0.795048
ECCAS	Gabon	1	1	1	1	1
ECCAS	Sao Tome and Principe	1	1	1	1	1
ECOWAS	Benin	0.842231	0.69401	0.778953	0.841557	0.677198
ECOWAS	Burkina Faso	0.906694	0.76561	0.861468	0.929007	0.753809
ECOWAS	Cabo Verde	0.78698	0.834837	0.799468	0.831876	0.739347
ECOWAS	Côte d'Ivoire	1	1	1	1	1
ECOWAS	Guinea	0.959609	0.894847	0.914042	0.972128	0.849929
ECOWAS	Niger	0.676814	0.68106	0.780878	0.859889	0.785338
ECOWAS	Nigeria	1	1	1	1	1
ECOWAS	Sierra Leone	1	1	1	1	1
ECOWAS	Togo	0.806542	0.725959	0.782101	0.838313	0.670061
SADC	Botswana	0.907452	0.979063	0.99194	0.995807	0.915608
SADC	Eswatini	1	1	1	1	1
SADC	Lesotho	0.803581	0.763281	0.851603	0.87628	0.787637
SADC	Mauritius	1	1	1	1	1
SADC	Mozambique	0.758815	0.604946	0.637554	0.733512	0.621781
SADC	South Africa	0.689414	0.916572	0.709216	0.909235	0.653715
SADC	Zimbabwe	0.969556	0.614813	0.828893	0.970121	0.75642
Geomean		**0.909655**	**0.879516**	**0.912368**	**0.94727**	**0.872158**

The Table 22 Presents capital service efficiency scores across five African regional blocs (AMU, EAC, ECCAS, ECOWAS, and SADC) from 2000 to 2019 and summary statistics for each regional bloc, including the mean, median, standard deviation, minimum, and maximum efficiency scores. Mean scores range from 0.86281 for SADC to 0.990885 for EAC, indicating variations in capital service efficiency across the blocs. Standard deviations show the degree of variability within each bloc. Higher standard deviations suggest greater variability in efficiency scores.

ANOVA is conducted to test for significant differences in efficiency scores among the regional blocs. The F-statistic is 59.20013 with a p-value of 5.53E-25, indicating a significant difference in efficiency scores among the blocs. The mean efficiency scores vary across the regional blocs, suggesting differences in the utilization of capital services. EAC has the highest mean efficiency score (0.990885), followed by AMU (0.907258), ECCAS (0.934865), ECOWAS (0.871938), and SADC (0.86281). Despite variability within each bloc (as indicated by standard deviations), the differences among bloc means are significant, as evidenced by the low p-value from the ANOVA. The efficiency scores fluctuate over the years within each bloc, reflecting potential changes in economic conditions, policies, and other factors. Some blocs exhibit increasing trends (e.g., EAC), while others show fluctuations or relatively stable trends. Variations in capital service efficiency among regional blocs may influence economic growth, investment attractiveness, and regional integration efforts. Understanding these differences can inform policymakers and stakeholders about areas needing improvement and facilitate benchmarking against other blocs. The Table 21 provides valuable insights into the variations in capital service efficiency among African regional blocs.

Table 22: Capital Service Efficiency Scores

Years	AMU	EAC	ECCAS	ECOWAS	SADC
2000	0.872507	1	0.964857	0.830358	0.754931
2001	0.872057	1	1	0.877406	0.809855
2002	0.875197	1	1	0.862703	0.764371
2003	0.884034	1	0.948162	0.864731	0.830789
2004	0.888569	1	1	0.843442	0.867775
2005	0.89241	1	0.946493	0.846033	0.872404
2006	0.904237	1	0.94316	0.876448	0.829318
2007	0.93411	1	0.930605	0.863808	0.885424
2008	0.916151	1	0.926486	0.888863	0.860949
2009	0.936524	1	0.909546	0.8742	0.890881
2010	0.946492	1	0.887858	0.869851	0.899939
2011	0.947738	0.975907	0.905978	0.864488	0.908111
2012	0.92835	0.976995	0.91346	0.883494	0.909225
2013	0.946951	0.980176	0.920013	0.888772	0.89479
2014	0.909298	0.99483	0.911649	0.889938	0.931049
2015	0.893851	0.983158	0.881577	0.892093	0.885747
2016	0.917723	0.979439	0.886863	0.887374	0.875114
2017	0.876212	0.995108	0.918213	0.885754	0.869818
2018	0.902527	0.967896	0.966614	0.879483	0.867544
2019	0.900212	0.96419	0.935758	0.869523	0.848174
Geomean	**0.906907**	**0.990811**	**0.934192**	**0.87178**	**0.861609**

Summary Statistics of Capital Service Efficiency (2000-2019)

Regional Bloc	Count	Sum	Mean	Variance	Standard Deviation	Minimum	Maximum
AMU	20	18.14515	0.907258	0.000672	0.025932	0.872057	0.947738
EAC	20	19.8177	0.990885	0.000153	0.012378	0.96419	1
ECCAS	20	18.69729	0.934865	0.001338	0.036584	0.881577	1
ECOWAS	20	17.43876	0.871938	0.000287	0.016946	0.830358	0.892093
SADC	20	17.25621	0.86281	0.002101	0.045841	0.754931	0.931049

ANOVA Analysis of Capital Service Efficiency (2000-2019)

Source of Variation	Sum of Squares (SS)	Degrees of Freedom (df)	Mean Squares (MS)	F-Statistic	P-value	Critical F
Between Groups	0.215613	4	0.053903	59.20013	5.53E-25	2.467494
Within Groups	0.0865	95	0.000911			
Total	0.302113	99				

The Table 23 presents labour efficiency scores across five African regional blocs (AMU, EAC, ECCAS, ECOWAS, and SADC) over the period from 2000 to 2019. The mean labour efficiency scores vary across the regional blocs, ranging from 0.84299465 for SADC to 0.9694416 for EAC. The median scores also differ, with EAC having the highest median score of 1, while the others are slightly lower. Standard deviations show the degree of variability within each regional bloc. EAC has the highest standard deviation, indicating higher variability in labour efficiency scores compared to other blocs. The minimum and maximum scores provide insights into the range of labour efficiency observed within each bloc over the specified period.

The ANOVA results indicate a highly significant difference in labour efficiency scores among the regional blocs ($p < 0.05$). Between groups, the sum of squares (SS) is 67240100, with 5 degrees of freedom, resulting in a mean square (MS) of 13448019.94 and an F-statistic of 2305078. This large F-statistic and low p-value (1.8E-283) suggest strong evidence against the null hypothesis, indicating significant differences in labour efficiency among the blocs. Within groups, the sum of squares (SS) is 665.0857 with 114 degrees of freedom.

The data reveals notable variations in labour efficiency across the African regional blocs, with some blocs consistently outperforming others over the years. EAC consistently demonstrates the highest labour efficiency scores, indicating a potentially more effective utilization of labor resources within that bloc. SADC consistently exhibits lower labour efficiency scores compared to other blocs, suggesting challenges or inefficiencies in labor utilization within the region. The significant differences observed among the blocs highlight the importance of understanding and addressing factors influencing labour efficiency, such as education, skill development, labor market policies, and technological advancement. Policymakers and stakeholders could use these findings to identify areas for improvement and implement targeted interventions to enhance labour productivity and economic growth within the African regional blocs. The analysis underscores the importance of labor efficiency in driving economic development and regional integration efforts across Africa, emphasizing the need for tailored strategies to address efficiency disparities among the regional blocs.

Table 23: Labour efficiency scores across the regional blocs from 2000-2019

Years	**AMU**	**EAC**	**ECCAS**	**ECOWAS**	**SADC**
2000	0.93215	1	0.976295	0.861613	0.80737
2001	0.935649	1	1	0.879603	0.812945
2002	0.935618	1	1	0.890987	0.823521

2003	0.945651	1	0.995718	0.887514	0.83267
2004	0.944602	1	1	0.864359	0.846413
2005	0.942663	1	0.998436	0.865811	0.847475
2006	0.950329	1	0.996215	0.882504	0.849299
2007	0.963472	1	0.981579	0.874997	0.849574
2008	0.953001	1	0.979796	0.899177	0.866686
2009	0.956282	1	0.971087	0.874022	0.90632
2010	0.965005	1	0.955126	0.860977	0.905876
2011	0.967825	0.94739	0.943472	0.854031	0.87669
2012	0.963647	0.929678	0.943079	0.86156	0.889135
2013	0.972454	0.907983	0.91996	0.868098	0.84982
2014	0.966004	0.955672	0.903704	0.861515	0.822313
2015	0.955147	0.910054	0.910765	0.851918	0.823117
2016	0.962923	0.895271	0.90507	0.836587	0.814531
2017	0.943531	0.984011	0.886273	0.835273	0.808017
2018	0.943532	0.926988	0.925954	0.834497	0.822546
2019	0.931347	0.931785	0.936765	0.838679	0.805575
Geomean	**0.951459**	**0.968686**	**0.955732**	**0.863992**	**0.842432**

Summary Statistics of Labour Efficiency (2000-2019):

	AMU	EAC	ECCAS	ECOWAS	SADC
Mean	0.951542	0.969442	0.9564647	0.864186	0.842995
Median	0.951665	1	0.9631065	0.862986	0.839542
Standard Deviation	0.012836	0.038911	0.038246013	0.018787	0.031858
Minimum	0.931347	0.895271	0.886273	0.834497	0.805575
Maximum	0.972454	1	1	0.899177	0.90632

ANOVA Analysis of Labour Efficiency (2000-2019):

Source of Variation	Sum of Squares (SS)	Degrees of Freedom (df)	Mean Squares (MS)	F-Statistic	P-value	Critical F
Between Groups	67240100	5	13448019.94	2305078	1.8E-283	2.293911
Within Groups	665.0857	114	5.834084908			

The Table 24 presents energy use efficiency scores across five African regional blocs (AMU, EAC, ECCAS, ECOWAS, and SADC) over the period from 2000 to 2019.

The mean energy use efficiency scores vary across the regional blocs, ranging from 0.826614 for SADC to 0.984246 for EAC. The standard error provides a measure of the variability of the mean estimates. The median scores also differ, with EAC having the highest median score of 1, while the others are slightly lower. Standard deviations show the degree of variability within each regional bloc. ECOWAS has the highest standard deviation, indicating higher variability in energy use efficiency scores compared to other blocs. The minimum and maximum scores provide insights into the range of energy use efficiency observed within each bloc over the specified period.

The ANOVA results indicate a highly significant difference in energy use efficiency scores among the regional blocs ($p < 0.05$). Between groups, the sum of squares (SS) is 0.370293, with 4 degrees of freedom, resulting in a mean square (MS) of 0.092573 and an F-statistic of 157.9369. This large F-statistic and low p-value (4.49E-41) suggest strong evidence against the null hypothesis, indicating significant differences in energy use efficiency among the blocs. Within groups, the sum of squares (SS) is 0.055683 with 95 degrees of freedom.

The data reveals notable variations in energy use efficiency across the African regional blocs, with some blocs consistently outperforming others over the years. EAC consistently demonstrates the highest energy use efficiency scores, indicating a potentially more effective utilization of energy resources within that bloc. SADC consistently exhibits lower energy use efficiency scores compared to other blocs, suggesting challenges or inefficiencies in energy utilization within the region. The significant differences observed among the blocs highlight the importance of understanding and addressing factors influencing energy use efficiency, such as energy policies, technological advancements, and energy infrastructure development. Policymakers and stakeholders could use these findings to identify areas for improvement and implement targeted interventions to enhance energy use efficiency and promote sustainable development within the African regional blocs.

The analysis underscores the importance of energy use efficiency in driving economic development and environmental sustainability across Africa, emphasizing the need for tailored strategies to address efficiency disparities among the regional blocs.

Table 24: Energy Use efficiency scores across the regional blocs from 2000-2019

Years	**AMU**	**EAC**	**ECCAS**	**ECOWAS**	**SADC**
2000	0.942402	1	0.98295	0.898255	0.774314
2001	0.943387	1	1	0.91408	0.822976
2002	0.942762	1	1	0.922865	0.7828
2003	0.951774	1	0.991975	0.912561	0.831825
2004	0.955835	1	1	0.851706	0.84508
2005	0.945403	1	0.963657	0.848821	0.839963
2006	0.95647	1	0.974365	0.895931	0.791546
2007	0.960512	1	0.960219	0.853605	0.825232
2008	0.951541	1	0.956299	0.87495	0.807718
2009	0.951176	1	0.934025	0.853017	0.866819
2010	0.960919	1	0.938039	0.834693	0.867185
2011	0.96777	0.961208	0.916	0.833865	0.831982
2012	0.96382	0.954408	0.91397	0.833061	0.834199
2013	0.974427	0.955471	0.93723	0.850905	0.824614
2014	0.972537	0.99342	0.918684	0.851869	0.845389
2015	0.971202	0.954622	0.91772	0.838609	0.812144
2016	0.979632	0.938294	0.926327	0.832233	0.8242
2017	0.964041	0.990684	0.95113	0.867607	0.83539

2018	0.963254	0.964147	0.965732	0.874618	0.848487
2019	0.959324	0.972671	0.973939	0.887258	0.820413
Geomean	**0.958849**	**0.984024**	**0.95567**	**0.866055**	**0.826268**

Summary Statistics of Energy Use Efficiency (2000-2019)

	AMU	EAC	ECCAS	ECOWAS	SADC
Mean	0.958909	0.984246	0.956113	0.866525	0.826614
Standard Error	0.002459	0.004766	0.006678	0.006588	0.005457
Median	0.959918	1	0.958259	0.853311	0.828529
Standard Deviation	0.010999	0.021315	0.029864	0.02946	0.024406
Minimum	0.942402	0.938294	0.91397	0.832233	0.774314
Maximum	0.979632	1	1	0.922865	0.867185

ANOVA Analysis of Energy Use Efficiency (2000-2019)

Source of Variation	Sum of Squares (SS)	Degrees of Freedom (df)	Mean Squares (MS)	F-Statistic	P-value	Critical F
Between Groups	0.370293	4	0.092573	157.9369	4.49E-41	2.467494
Within Groups	0.055683	95	0.000586			

The Table 25 presents GDP efficiency scores across five African regional blocs (AMU, EAC, ECCAS, ECOWAS, and SADC) over the period from 2000 to 2019.

The mean GDP efficiency scores vary across the regional blocs, ranging from 0.90463 for SADC to 0.994054 for EAC. The standard deviation provides insights into the variability of GDP efficiency scores within each regional bloc. ECCAS has the highest standard deviation, indicating greater variability compared to other blocs. The minimum and maximum scores represent the range of GDP efficiency observed within each bloc over the specified period.

The ANOVA results indicate a highly significant difference in GDP efficiency scores among the regional blocs ($p < 0.05$). Between groups, the sum of squares (SS) is 0.131035, with 4 degrees of freedom, resulting in a mean square (MS) of 0.032759 and an F-statistic of 59.22984. This large F-statistic and low p-value (5.44E-25) suggest strong evidence against the null hypothesis, indicating significant differences in GDP efficiency among the blocs. Within groups, the sum of squares (SS) is 0.052542 with 95 degrees of freedom.

The data reveals notable variations in GDP efficiency across the African regional blocs, with some blocs consistently outperforming others over the years. EAC consistently demonstrates the highest GDP efficiency scores, indicating a potentially more effective utilization of economic resources within that bloc. SADC consistently exhibits lower GDP efficiency scores compared to other blocs, suggesting challenges or inefficiencies in economic resource allocation and utilization within the region. The significant differences observed among the blocs highlight the importance of understanding and addressing factors influencing GDP efficiency, such as economic policies, investment climate, infrastructure development, and governance. Policymakers and stakeholders could use these findings to identify areas for improvement and implement targeted interventions to enhance GDP efficiency and promote economic growth and development within the African regional blocs.

The analysis underscores the importance of GDP efficiency in driving economic development and regional integration efforts across Africa, emphasizing the need for tailored strategies to address efficiency disparities among the regional blocs.

Table 25: GDP efficiency scores across the regional blocs from 2000-2019

Years	**AMU**	**EAC**	**ECCAS**	**ECOWAS**	**SADC**
2000	0.968236	1	0.996328	0.920426	0.836822
2001	0.963809	1	1	0.926244	0.844856
2002	0.963027	1	1	0.936839	0.848552
2003	0.973168	1	0.997976	0.930227	0.849524
2004	0.975017	1	1	0.920473	0.86654
2005	0.971977	1	0.999243	0.915077	0.861801
2006	0.97722	1	0.998389	0.937213	0.868789
2007	0.979907	1	0.992177	0.932686	0.869985
2008	0.975855	1	0.988348	0.937831	0.899224
2009	0.973936	1	0.988149	0.910363	0.949356
2010	0.980369	1	0.982642	0.901902	0.955319
2011	0.984098	0.974137	0.988592	0.897915	0.964188
2012	0.982682	0.986269	0.990604	0.907269	0.967293
2013	0.987166	0.993456	0.962673	0.914878	0.956224
2014	0.985592	0.997403	0.953288	0.907906	0.941343
2015	0.982789	0.995428	0.956545	0.914981	0.936163
2016	0.987963	0.985436	0.963949	0.922344	0.933846
2017	0.978076	0.996445	0.916354	0.912972	0.921232
2018	0.973766	0.977657	0.979508	0.916392	0.921579
2019	0.970677	0.974844	0.98476	0.918171	0.899969
Geomean	**0.976741**	**0.994014**	**0.981747**	**0.919036**	**0.903558**

Summary Statistics of GDP Efficiency (2000-2019):

	AMU	**EAC**	**ECCAS**	**ECOWAS**	**SADC**
Mean	0.976767	0.994054	0.981976	0.919105	0.90463
Median	0.976538	1	0.98847	0.917282	0.910601
Standard Deviation	0.007198	0.009112	0.021512	0.011585	0.045095
Minimum	0.963027	0.974137	0.916354	0.897915	0.836822
Maximum	0.987963	1	1	0.937831	0.967293

ANOVA Analysis of GDP Efficiency (2000-2019):

Source of Variation	**Sum of Squares (SS)**	**Degrees of Freedom (df)**	**Mean Squares (MS)**	**F-Statistic**	**P-value**	**Critical F**
Between Groups	0.131035	4	0.032759	59.22984	5.44E-25	2.467494

Source of Variation	Sum of Squares (SS)	Degrees of Freedom (df)	Mean Squares (MS)	F-Statistic	P-value	Critical F
Within Groups	0.052542	95	0.000553			

The Table 26 presents CO2 efficiency scores across five African regional blocs (AMU, EAC, ECCAS, ECOWAS, and SADC) over the period from 2000 to 2019. The mean CO2 efficiency scores vary across the regional blocs, ranging from 0.828081 for SADC to 0.989478 for EAC. The standard deviation provides insights into the variability of CO2 efficiency scores within each regional bloc. ECOWAS has the highest standard deviation, indicating greater variability compared to other blocs. The minimum and maximum scores represent the range of CO2 efficiency observed within each bloc over the specified period.

The ANOVA results indicate a highly significant difference in CO2 efficiency scores among the regional blocs ($p < 0.05$). Between groups, the sum of squares (SS) is 0.371742, with 4 degrees of freedom, resulting in a mean square (MS) of 0.092935 and an F-statistic of 125.4465. This large F-statistic and low p-value (5.04E-37) suggest strong evidence against the null hypothesis, indicating significant differences in CO2 efficiency among the blocs. Within groups, the sum of squares (SS) is 0.07038 with 95 degrees of freedom.

The data reveals notable variations in CO2 efficiency across the African regional blocs, with some blocs consistently demonstrating higher efficiency in reducing CO2 emissions over the years. EAC consistently exhibits the highest CO2 efficiency scores, indicating better performance in reducing CO2 emissions per unit of economic output within that bloc. SADC consistently shows lower CO2 efficiency scores compared to other blocs, suggesting challenges or inefficiencies in reducing CO2 emissions within the region. The significant differences observed among the blocs highlight the importance of understanding and addressing factors influencing CO2 efficiency, such as environmental policies, renewable energy adoption, technological advancements, and industrial practices. Policymakers and stakeholders could utilize these findings to identify areas for improvement and implement targeted interventions to enhance CO2 efficiency and promote sustainable development within the African regional blocs.

The analysis underscores the importance of CO2 efficiency in addressing climate change and promoting sustainable development across Africa, emphasizing the need for concerted efforts to reduce emissions and enhance environmental sustainability within the regional blocs.

Table 26: CO2 efficiency scores across the regional blocs from 2000-2019

Years	AMU	EAC	ECCAS	ECOWAS	SADC
2000	0.954022	1	0.995996	0.905778	0.787586
2001	0.940884	1	1	0.906711	0.840012
2002	0.943013	1	1	0.915549	0.795807
2003	0.955312	1	0.99684	0.91794	0.847973
2004	0.957877	1	1	0.906954	0.860392
2005	0.956697	1	0.998821	0.906985	0.857493
2006	0.960914	1	0.997831	0.917557	0.809529
2007	0.964021	1	0.985861	0.914966	0.861212
2008	0.963002	1	0.984907	0.920043	0.83068
2009	0.94987	1	0.983404	0.896619	0.861946
2010	0.971005	1	0.979545	0.881312	0.858364
2011	0.974795	0.982921	0.986345	0.873959	0.846515
2012	0.968073	0.99005	0.987138	0.872469	0.846583
2013	0.973897	0.986307	0.978585	0.887059	0.820118
2014	0.950261	0.985435	0.969146	0.882614	0.840353
2015	0.941118	0.981606	0.971782	0.880828	0.804675
2016	0.956858	0.971005	0.973342	0.868736	0.808691
2017	0.927049	0.955434	0.870447	0.776701	0.792675
2018	0.918976	0.964495	0.922367	0.820641	0.806392
2019	0.910353	0.972313	0.942003	0.82353	0.784622
Geomean	**0.951745**	**0.989382**	**0.9757**	**0.883038**	**0.827654**

Summary Statistics of CO2 Efficiency (2000-2019):

	AMU	EAC	ECCAS	ECOWAS	SADC
Mean	0.9519	0.989478	0.976218	0.883848	0.828081
Median	0.956005	1	0.985384	0.891839	0.835346
Standard Deviation	0.017527	0.014084	0.03186	0.037985	0.027216
Minimum	0.910353	0.955434	0.870447	0.776701	0.784622
Maximum	0.974795	1	1	0.920043	0.861946

ANOVA Analysis of CO2 Efficiency (2000-2019):

Source of Variation	Sum of Squares (SS)	Degrees of Freedom (df)	Mean Squares (MS)	F-Statistic	P-value	Critical F
Between Groups	0.371742	4	0.092935	125.4465	5.04E-37	2.467494
Within Groups	0.07038	95	0.000741			

The Fig 5 presents GDP efficiency scores across various African regional blocs from 2000 to 2019. Overall, there seems to be a fluctuating trend in GDP efficiency scores across the years for all regional blocs. While some years show slight improvements, others show slight declines. However, there isn't a clear linear trend observable over the period.

EAC (East African Community) consistently maintains a GDP efficiency score of 1 (or 100%) throughout the years, indicating a high level of efficiency in utilizing GDP within the bloc. AMU (Arab Maghreb Union) and SADC (Southern African Development Community) also show relatively high and consistent GDP efficiency scores, albeit slightly below 1. ECCAS (Economic Community of Central African States) and ECOWAS (Economic Community of West African States) exhibit more variability in their GDP efficiency scores, with some years showing scores close to 1 and others slightly lower. The variability in GDP efficiency scores might be influenced by various external factors such as economic policies, regional trade agreements, infrastructure development, political stability, and global economic conditions.

Overall, the Fig. 5 provides valuable insights into the GDP efficiency trends across African regional blocs, highlighting areas of strength and potential areas for improvement in economic performance and resource utilization.

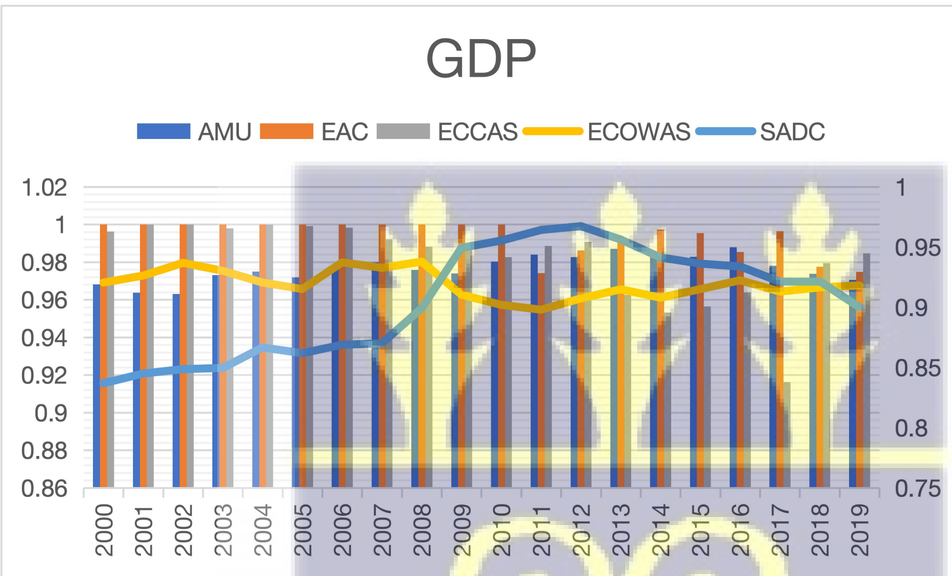

Figure 5: GDP Trend Across the Regional Blocs

The Fig. 6 presents energy use efficiency scores across various African regional blocs from 2000 to 2019. Energy use efficiency scores vary across the years and regional blocs. There are fluctuations in scores over time, indicating changes in the efficiency of energy utilization within each bloc. EAC (East African Community) maintains a consistently high energy use efficiency score of 1 (or 100%) throughout the years, indicating optimal utilization of energy resources within the bloc. AMU (Arab Maghreb Union), ECCAS (Economic Community of Central African States), ECOWAS (Economic Community of West African States), and SADC

(Southern African Development Community) demonstrate fluctuations in energy use efficiency scores over the years, with some years exhibiting higher efficiency than others. ECOWAS and SADC show lower energy use efficiency scores compared to other regional blocs, indicating potential areas for improvement in energy utilization within these regions. The variability in energy use efficiency scores could be influenced by factors such as energy infrastructure development, adoption of renewable energy sources, energy conservation measures, industrial processes, and overall economic activity within each regional bloc. Policymakers within each regional bloc could use these findings to identify areas for improvement in energy utilization and implement policies aimed at enhancing energy efficiency. This may include investments in renewable energy projects, promoting energy conservation and efficiency measures, and implementing regulations to reduce energy wastage. Sustainability considerations: Improving energy use efficiency is crucial for promoting sustainable development and mitigating environmental impacts such as greenhouse gas emissions and climate change. Policymakers should prioritize sustainable energy strategies to ensure long-term economic and environmental sustainability.

The fig. 6 provides valuable insights into energy use efficiency trends across African regional blocs, highlighting areas of strength and potential areas for improvement in energy utilization and resource management. Addressing inefficiencies in energy use can contribute to economic growth, environmental sustainability, and overall regional development.

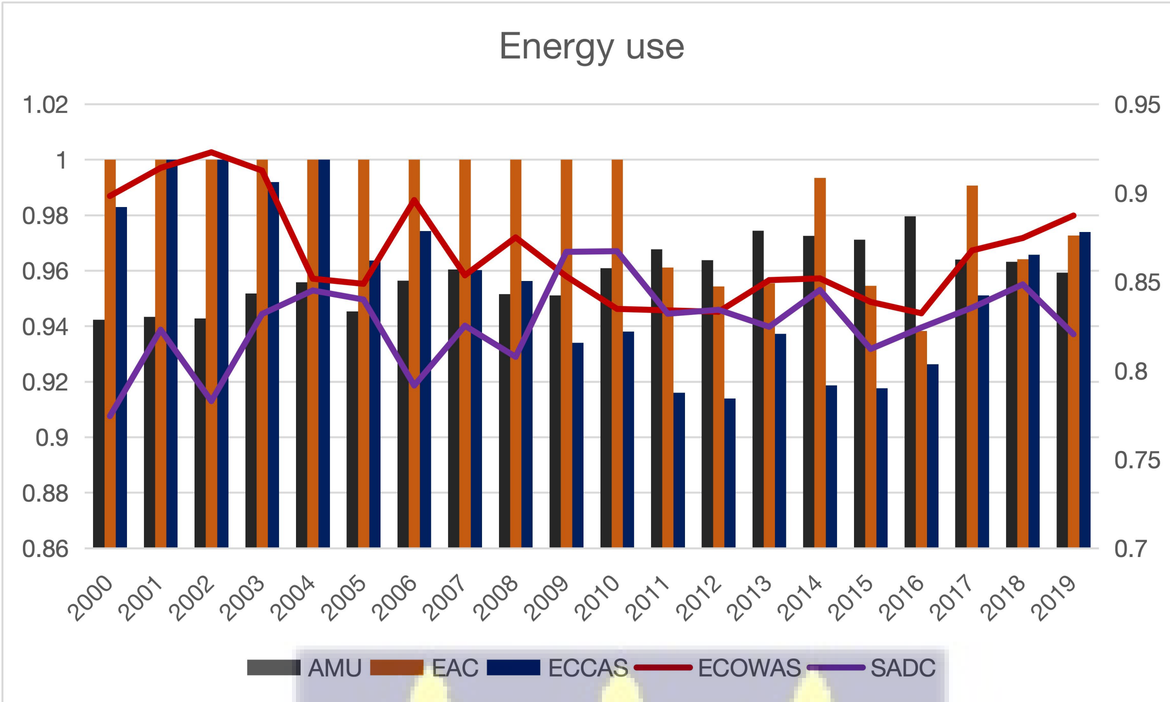

Figure 6: Energy Use Trend Across the Regional Blocs

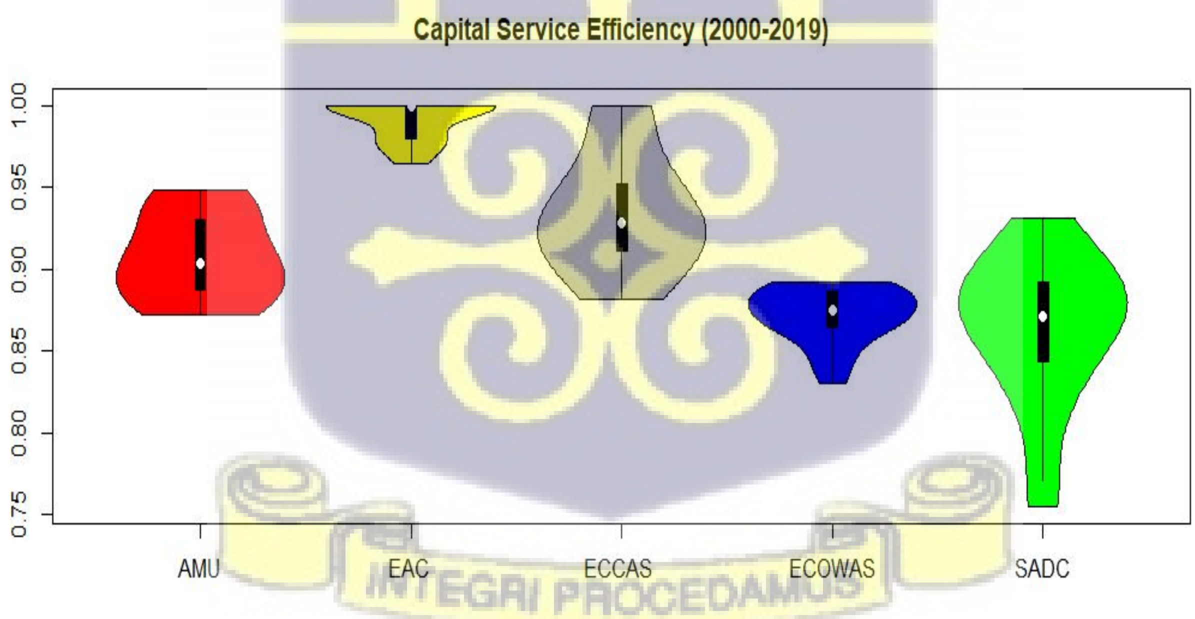

Figure 7: Capital Service Trend Across the Regional Blocs

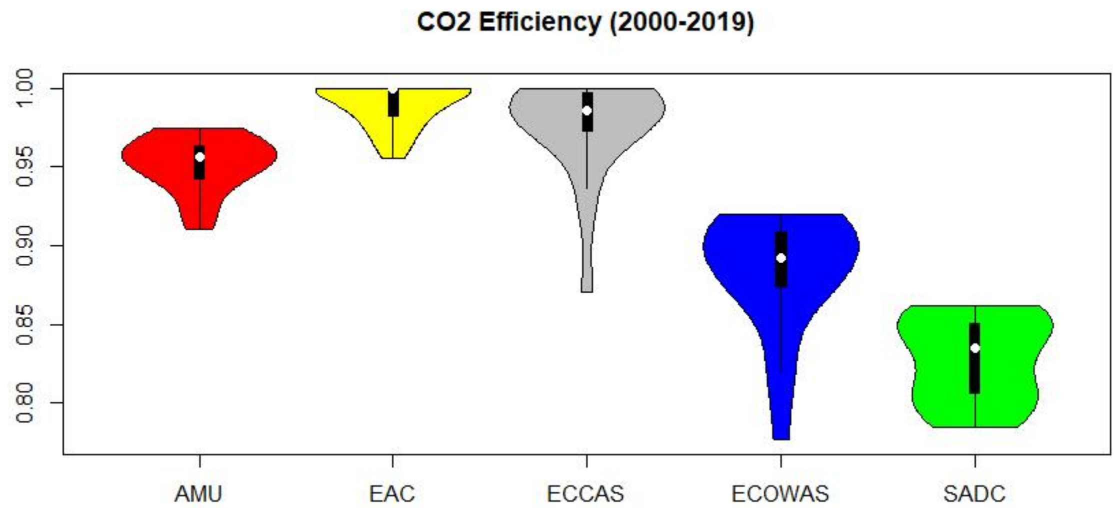

Figure 8: CO2 Trend Across the Regional Blocs

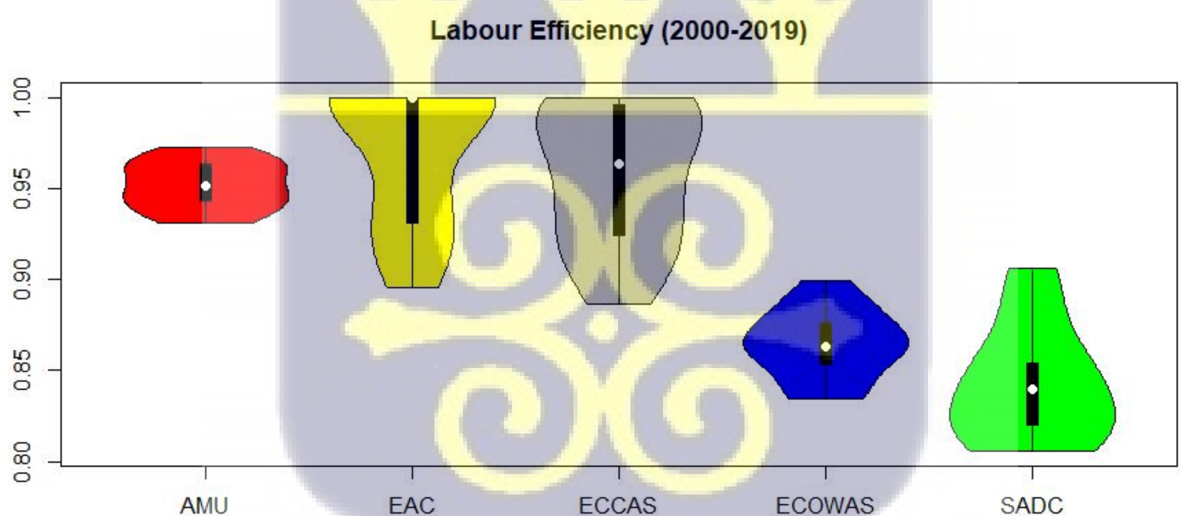

Figure 9: Labour Trend Across the Regional Blocs

The figure 7 shows Capital Service trend across the regional blocs. The violin plot shows that EAC region again shows very high capital service efficiency, with near-perfect scores and minimal variability. This indicates a highly efficient use of capital services over the entire period.

AMU's Capital service efficiency in AMU is lower than its labour or CO2 efficiency, with scores concentrated around 0.87 to 0.93. There is a bit more variability in capital use, but overall, it reflects a solid performance. ECCAS shows moderate fluctuations in capital service efficiency, with most scores ranging between 0.91 and 0.96. This indicates a relatively stable, but slightly less consistent use of capital services compared to labor and CO2 efficiency. ECOWAS shows notable variability in capital efficiency, with scores mostly between 0.82 and 0.89. This suggests less efficient use of capital services compared to labor and CO2 efficiency, with frequent dips in performance. The SADC region shows considerable variation in capital service efficiency, with scores generally below 0.9. The wide distribution suggests SADC has struggled with efficient capital use, similar to its performance in CO2 and labor efficiency.

The figure 8 shows CO2 trend across the regional blocs. The violin plot shows EAC had perfect efficiency (score of 1) until around 2011, after which it slightly decreased. The narrow, flat shape reflects little variability during this period. The AMU region has relatively stable scores, but with minor variability. Its distribution shows a high concentration around 0.95, suggesting overall good efficiency but with occasional dips below that threshold. ECCAS displays moderate variability in CO2 efficiency scores, with a higher concentration near 1. Despite a few fluctuations, its scores generally hover near optimal efficiency. The plot indicates more variation for ECOWAS, with a wider spread. The scores fluctuate between 0.77 and 0.92, indicating occasional inefficiencies in CO2 management compared to other regions. The broadest distribution is seen in SADC, reflecting significant variability in CO2 efficiency. Scores range from around 0.78 to 0.86, indicating that SADC has struggled to maintain consistent performance in CO2 efficiency compared to other blocs.

The figure 8 shows labour trend across the regional blocs. The violin plot shows that EAC also starts with perfect labor efficiency but drops slightly after 2011. Similar to CO2, this reflects very efficient labor use initially, followed by a small decline. AMU shows a strong performance in labor efficiency, with scores consistently above 0.93. There is little variation, indicating stable labor productivity over time. ECCAS's labour efficiency shows some slight fluctuations, with most scores above 0.9. However, it has less variability than SADC and ECOWAS, suggesting moderate efficiency. Labour efficiency in ECOWAS fluctuates more significantly than ECCAS, especially during the mid-2000s. The distribution suggests occasional inefficiencies, with scores often falling below 0.9. The SADC region has the broadest distribution, indicating significant variability in labor efficiency scores. Scores range from around 0.81 to 0.91, implying less consistent labor productivity.

EAC consistently demonstrates high efficiency across all three dimensions (CO2, labor, and capital services) with minimal variability, indicating stable and effective resource use. AMU generally performs well in all three categories but shows more variation in capital service efficiency compared to labor and CO2. ECCAS maintains strong scores, especially in CO2 efficiency, but shows moderate variability in capital and labor efficiency. ECOWAS and SADC show the most variation in all three categories, indicating they struggle to maintain consistent efficiency levels, particularly in capital service use. SADC, in particular, exhibits the broadest distribution across all three metrics, suggesting inefficiencies and inconsistent performance.

This analysis highlights regional differences in resource use and efficiency, with some blocs, like EAC and AMU, demonstrating consistently high performance, while others, like ECOWAS and SADC, show more variability and room for improvement.

4.7 Energy Efficiency and external factors

4.7.1 Second stage data description

The study also sought to examine the significant impact of sub-regional groupings and other external factors on the energy efficiency of African states. In the first stage, energy efficiency is estimated, while the second stage involves regressing the estimated indices on environmental covariates to establish their influence on the regressand. This two-stage analysis is extensively documented in the literature on Data Envelopment Analysis (DEA) and stochastic frontier analysis (R. Banker et al., 2019; Daraio & Simar, 2007; Hoff, 2007; McDonald, 2009; Ramalho et al., 2010; Léopold Simar & Wilson, 2011, 2015). Drawing from the energy efficiency literature, the study identified several key variables as potential determinants of the dynamic cost productivity of African states. These include population (POP), carbon dioxide emissions (CO2), methane emissions (CH4), level of technology (TECH), renewable energy utilization (REN), inflation (INF), economic development (ED), foreign direct investment (FDI), degree of government intervention in economic activities (GOV), level of urbanization (URB), cost efficiency change (CEC), cost technological change (CTC), and affiliation to the major African regional blocs (proxied by AMU, EAC, ECCAS, ECOWAS, and SADC). By integrating these variables into our analysis framework, we aim to comprehensively understand the nuanced dynamics influencing energy efficiency patterns in African states. Through rigorous empirical investigation and statistical modeling, our study endeavors to contribute valuable insights to the discourse on sustainable development and energy policy in the region.

Table 27 presents the descriptive statistics of the variables used in the various second stage analysis. The descriptive statistics provided in Table 26 offer insights into the distribution and variability of the second stage variables, including Energy Efficiency, Population (POP), Carbon

Dioxide Emissions (CO2), Methane Emissions (CH4), Level of Technology (TECH), Renewable Energy Used (REN), Inflation (INF), Economic Development (ED), Foreign Direct Investments (FDI), Degree of Government Intervention in Economic Activities (GOV), and Level of Urbanization (URB).

The mean energy efficiency score is 0.920, with a standard deviation of 0.120. The minimum energy efficiency score is 0.547, and the maximum is 1.000, indicating substantial variability in energy efficiency levels across the observed entities. The mean population size is approximately 12,632,954, with a standard deviation of 12,275,324. The range of population sizes is wide, from 142,262 to 54,663,906. The mean CO2 emissions are approximately 6,734.020, with a standard deviation of 10,984.660. The mean CH4 emissions are approximately 13,024.492, with a standard deviation of 18,810.671. Both CO2 and CH4 emissions display considerable variability, as evidenced by their large standard deviations and wide ranges. The mean level of technology is approximately 457.084, with a standard deviation of 556.796. The mean proportion of renewable energy used is approximately 0.051, with a standard deviation of 0.058. These variables also exhibit significant dispersion, indicating variations in technological advancement and adoption of renewable energy sources. INF, ED, FDI, GOV, and URB demonstrate similar patterns of variability, with moderate to high standard deviations and wide ranges. The mean INF is approximately 7.648, with a standard deviation of 18.104. The mean ED is approximately 4,341.214, with a standard deviation of 4,114.055. The mean FDI is approximately 4.106, with a standard deviation of 6.015. The mean GOV is approximately 15.422, with a standard deviation of 6.087. The mean URB is approximately 40.857, with a standard deviation of 18.774.

This information is essential for understanding the dynamics of energy efficiency and its relationship with various socio-economic and environmental factors.

Table 27: Descriptive Statistic of the Second Stage Data

	Energy efficiency	*POP*	*CO2*	*CH4*	*TECH*	*REN*	*INF*	*ED*	*FDI*	*GOV*	*URB*
Mean	0.920	12632954	6734.020	13024.492	457.084	0.051	7.648	4341.214	4.106	15.422	40.857
Median	1.000	9521348	2510.062	7039.685	185.021	0.022	4.907	2993.588	2.511	14.938	38.084
Standard Deviation	0.120	12275324	10984.660	18810.671	556.796	0.058	18.104	4114.055	6.015	6.087	18.774
Minimum	0.547	142262	47.671	36.952	4.960	0.001	-60.496	616.802	-6.057	2.047	8.246
Maximum	1.000	54663906	61584.000	147533.000	2940.096	0.241	324.997	23536.248	46.494	41.888	88.976

Notes: POP=population, C02=carbon dioxide emissions, CH4= methane emission, TECH=level of technology, REN=renewable energy used, INF=inflation, ED= economic development, FDI= foreign direct investments, GOV= degree of government intervention in economic activities, URB=level of urbanization

The correlation matrix provided in Table 28 presents the pairwise correlations between the second stage variables, including Energy Efficiency, Population (POP), Carbon Dioxide Emissions (CO2), Methane Emissions (CH4), Level of Technology (TECH), Renewable Energy Used (REN), Inflation (INF), Economic Development (ED), Foreign Direct Investments (FDI), Degree of Government Intervention in Economic Activities (GOV), Urbanization Level (URB), as well as regional bloc indicators (EAC, ECOWAS, ECCAS, SADC, AMU).

Energy efficiency shows weak positive correlations with most variables, with the highest positive correlation observed with Economic Development (0.203) and Urbanization Level (0.160). Energy efficiency has weak negative correlations with a few variables, such as Level of Technology (-0.179) and Degree of Government Intervention (-0.005). Population (POP) has a weak positive correlation with CO2 emissions (0.522) and CH4 emissions (0.412). CO2 emissions and CH4 emissions show a moderate positive correlation (0.110). Level of Technology (TECH) demonstrates weak negative correlations with Population (POP) (-0.228) and Urbanization Level (URB) (-0.245). Renewable Energy Used (REN) displays a strong positive correlation with Population (0.791), indicating that as population increases, there's a tendency to use more renewable energy sources. Economic Development (ED) exhibits a strong positive correlation with Level of Technology (0.862), indicating that technological advancement often accompanies economic development. Economic Development (ED) also shows positive correlations with Urbanization Level (0.556) and Foreign Direct Investments (0.113). The correlations between regional bloc indicators (EAC, ECOWAS, ECCAS, SADC, AMU) and other variables vary, with no consistent pattern observed.

The correlation matrix provides insights into the relationships between energy efficiency and various socio-economic and environmental factors. Economic development, urbanization, and technological advancement appear to be positively associated with energy efficiency. Renewable energy usage shows a strong positive correlation with population size, suggesting the importance of renewable energy adoption in densely populated areas. The correlations between emissions (CO2 and CH4) and other variables highlight the complex interplay between population growth, economic development, and environmental sustainability. This analysis underscores the multidimensional nature of energy efficiency and emphasizes the need for holistic policies that consider socio-economic and environmental factors to promote sustainable development

Table 28: A correlation matrix for the second stage variables

	Energy efficiency	*POP*	*CO2*	*CH4*	*TECH*	*REN*	*INF*	*ED*	*FDI*	*GOV*	*URB*	*EAC*	*ECOWAS*	*ECCAS*	*SADC*	*AMU*
Energy efficiency	1.00															
POP	0.06	1.000														
CO2	0.057	0.522***	1.000													
CH4	-0.003	0.412***	0.110***	1.00												
TECH	0.179***	-0.23***	0.305***	-0.16***	1.00											
REN	-0.010	0.791***	0.487***	0.34***	-0.09	1.00										
INF	0.105*	0.055***	-0.01***	0.12**	0.01	0.06	1.00									
ED	0.203***	-0.277	0.201	-0.22***	0.86***	-0.10	-0.06***	1.00								
FDI	0.060	-0.088	-0.123	-0.07	-0.03	0.01	0.16	-0.07	1.00							
GOV	0.005	-0.19***	0.076	-0.29***	0.16**	-0.06	0.04	0.11**	0.04	1.00						
URB	0.160**	-0.25***	0.296	-0.13**	0.50***	-0.01	-0.02	0.56***	0.14*	-0.04	1.00					
EAC	-0.12*	0.241***	-0.110	-0.12**	-0.19***	0.28***	-0.04	-0.06	-0.00	0.07	-0.27***	1.00				
ECOWAS	-0.17***	-0.17***	-0.258	-0.13**	-0.33***	-0.26***	-0.09	-0.26***	0.01	-0.16**	-0.10	-0.41***	1.00			
ECCAS	0.140*	-0.112	-0.028	0.17***	0.05	-0.03	0.16***	0.06	0.08	-0.30***	0.33***	-0.32***	-0.34***	1.00		
SADC	0.224***	-0.30***	-0.126	-0.19***	0.41***	-0.22***	-0.01	0.29***	-0.08	0.55***	-0.09	-0.21***	-0.23***	-0.17***	1.00	
AMU	0.041	0.356***	0.709	0.34***	0.28***	0.25***	-0.01	0.11	-0.05	-0.01	0.20***	-0.21***	-0.23***	-0.17***	-0.11***	1.00

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

	Energy efficiency	POP	CO2	CH4	TECH	REN	INF	ED	FDI
Energy efficiency	1.00								
POP	0.06	1.00							
CO2	0.06	0.52	1.00						
CH4	0.00	0.41	0.11	1.00					
TECH	0.18	-0.23	0.31	-0.16	1.00				
REN	-0.01	0.79	0.49	0.34	-0.09	1.00			
INF	0.11	0.05	-0.01	0.12	0.01	0.06	1.00		
ED	0.20	-0.28	0.20	-0.21	0.86	-0.10	-0.06	1.00	
FDI	0.06	-0.09	-0.12	-0.07	-0.03	0.01	0.16	-0.07	
GOV	0.00	-0.19	0.08	-0.29	0.16	-0.06	0.04	0.11	
URB	0.16	-0.24	0.30	-0.13	0.50	-0.02	-0.02	0.56	
EAC	-0.12	0.24	-0.11	-0.12	-0.19	0.28	-0.04	-0.06	
ECOWAS	-0.17	-0.17	-0.26	-0.13	-0.33	-0.26	-0.09	-0.26	
ECCAS	0.14	-0.11	-0.03	0.17	0.05	-0.03	0.16	0.06	
SADC	0.22	-0.30	-0.13	-0.19	0.41	-0.22	-0.01	0.29	-

The regression analysis provided in Table 29 aims to explore the relationship between energy efficiency and various predictor variables. The coefficient of multiple determination (R Square) is 0.239, indicating that approximately 23.9% of the variability in energy efficiency can be explained by the predictor variables included in the model. The adjusted R Square value, which considers the number of predictors in the model, is 0.217, suggesting that the model's explanatory power remains significant even after accounting for the degrees of freedom. The standard error of the regression (Standard Error) is 0.106, representing the average distance that the observed values fall from the regression line. The ANOVA table evaluates the overall significance of the regression model. The F-statistic is 10.614, with a very low p-value (2.14E-22), indicating that the regression model is statistically significant at conventional significance levels. This suggests that at least one of the predictor variables has a significant linear relationship with energy efficiency. The coefficients represent the estimated effect of each predictor variable on energy efficiency, holding other variables constant. The intercept coefficient is 0.690, indicating the expected value of energy efficiency when all predictor variables are zero. Among the predictor variables, Population (POP), Level of Technology (TECH), Renewable Energy Used (REN), Economic Development (ED), Foreign Direct Investments (FDI), and Urbanization Level (URB) have statistically significant coefficients at conventional significance levels ($p < 0.05$). Positive coefficients (e.g., POP, TECH, ED, URB) suggest that an increase in these variables is associated with higher energy efficiency. Negative coefficients (e.g., REN, INF, FDI, GOV) suggest that an increase in these variables is associated with lower energy efficiency. The coefficients for the regional bloc indicators (EAC, ECOWAS, ECCAS, SADC, AMU) are mostly non-significant, indicating that membership in these blocs does not have a statistically significant effect on energy efficiency in this model.

The regression analysis provides valuable insights into the factors influencing energy efficiency in the context of the study. Policies aimed at improving energy efficiency should focus on variables with significant coefficients, such as Population, Level of Technology, Renewable Energy Use, Economic Development, Foreign Direct Investments, and Urbanization. However, it's essential to interpret the results cautiously, considering potential limitations such as omitted variable bias, multicollinearity, and endogeneity.

Table 29: Regression Analysis

Regression Statistics	
Multiple R	0.489222
R Square	0.239339
Adjusted R Square	0.216789
Standard Error	0.106291

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	15	1.798729	0.119915	10.61403	2.14E-22
Residual	506	5.71669	0.011298		
Total	521	7.515419			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.690148	0.115989	5.950133	5.01E-09
POP	6.08E-09	8.5E-10	7.155055	2.95E-12
CO2	-1.7E-06	9.01E-07	-1.8336	0.067301
CH4	-5.5E-07	3.5E-07	-1.58067	0.114577
TECH	-6.7E-05	2.12E-05	-3.18458	0.001539
REN	-0.67166	0.15149	-4.43373	1.14E-05
INF	0.000634	0.00027	2.349048	0.019205
ED	1.02E-05	2.65E-06	3.839931	0.000139
FDI	0.001751	0.000841	2.080985	0.037938
GOV	-0.0018	0.001081	-1.66111	0.097311
URB	0.001628	0.000397	4.100719	4.8E-05
EAC	0.107912	0.112857	0.956188	0.339434
ECOWAS	0.106758	0.11242	0.949635	0.342751
ECCAS	0.157641	0.111316	1.416163	0.157343
SADC	0.287208	0.111637	2.572688	0.010375
AMU	0.1555	0.108679	1.430819	0.153099

The Theory of Planned Behavior (TPB) and the Resource-Based Theory (RBT) provide valuable insights that support the findings of this study on the impact of regional blocs on the energy efficiency patterns of African states.

The TPB posits that an individual's behavior is influenced by their attitudes, subjective norms, and perceived behavioral control. Applied to this study, the TPB helps understand how the attitudes and perceptions of policymakers, businesses, and other stakeholders within African states influence their behavior towards energy efficiency. Findings from the study reveal diverse energy efficiency patterns across African states, indicating varying levels of commitment and prioritization towards sustainable energy practices. The TPB suggests that these differences may stem from variations in attitudes and perceptions regarding the importance of energy efficiency, as well as the perceived control individuals and organizations have over implementing energy-saving measures. For example, countries with strong political will and supportive policy frameworks may exhibit higher levels of energy efficiency, driven by positive attitudes towards sustainability and environmental responsibility. Conversely, states facing economic constraints or lacking policy incentives may demonstrate lower energy efficiency levels due to perceived barriers and limited control over resource allocation.

RBT emphasizes the role of internal resources, capabilities, and competencies in shaping competitive advantage and organizational performance. Applied to the context of this study, RBT provides insights into how the allocation and utilization of resources influence energy efficiency outcomes within African states. The study's findings highlight the importance of various resources, such as technological advancements, renewable energy sources, and economic development, in determining energy efficiency patterns. Countries with access to abundant renewable energy resources or advanced technologies may exhibit higher energy efficiency levels, leveraging these resources as strategic assets. Moreover, RBT suggests that the effective management and allocation of resources contribute to sustainable competitive advantage. African states that effectively harness their resources through proactive policies, investments, and collaborations are likely to achieve greater energy efficiency outcomes, driving economic growth and environmental sustainability.

The Theory of Planned Behavior and Resource-Based Theory offer complementary perspectives on the complex interplay between individual behavior, organizational capabilities, and environmental outcomes in the context of energy efficiency in African states. By integrating insights from these theories, policymakers and stakeholders can develop targeted interventions and strategies to promote sustainable energy practices and enhance overall environmental performance across the continent.

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This concluding chapter is structured into three sections to encapsulate the essence of the study. The first section succinctly outlines the objectives and highlights the key findings. Following this, the second section derives conclusions from these findings, aligning them with the initially set objectives. Lastly, the chapter offers recommendations for policy and practice, along with suggestions for future research directions.

5.2 Summary of the Study

The study aims to shed light on the intricate factors influencing energy efficiency in African states and to contribute significantly to the formulation of effective policies and strategies geared towards fostering sustainable energy practices and environmental conservation throughout the continent. Despite the recognized positive correlation between energy performance and economic growth, Africa has historically exhibited low energy consumption levels relative to global standards, yet marred by inefficiencies and hindered economic development. Recognizing the imperative set by the United Nations to enhance economic, social, and technological growth through sustainable resource consumption and production, the study underscores the pressing need to delve into the dynamics of energy efficiency within the African context.

While numerous studies have previously examined aspects of energy efficiency in Africa, many have overlooked the critical consideration of the costs associated with energy production and consumption—a pivotal factor in ensuring the accessibility of affordable energy for all by 2030, in line with the 7th Sustainable Development Goal (SDG). In this regard, the present study makes a distinct and noteworthy contribution to policy formulation, practical applications, and academic research by filling this gap and addressing the multifaceted dimensions of energy efficiency.

Moreover, unlike its predecessors, the current study adopts a comprehensive approach by examining the influence of potential environmental covariates on energy efficiency. Through an extended second-stage DEA analysis coupled with multiple robust econometric techniques, the study conducts a thorough investigation, ensuring methodological rigor and cross-validation of findings.

The study's sample, comprising 32 African states across all five sub-regions, spans the period from 2000 to 2019. Data on crucial inputs such as capital services, labor, energy consumption, and outputs including real GDP and CO2 emissions were meticulously sourced from reputable databases such as the Penn World Tables (PWT version 9.10) and the US Energy Information Administration (EIA). Additionally, primary energy consumption inputs were derived from the EIA, while input prices were computed based on information from the PWT 9.10 and EIA. External variables for the second stage analysis were sourced from the World Development Indicators (WDI).

Employing a two-stage approach consisting of non-parametric DEA analysis in the first stage and econometric regression analysis in the second, the study meticulously analyzes and interprets the data. Descriptive statistics of pooled data and regional blocs in Africa are presented, followed by tests of return to scale and correlations between inputs and outputs. Through these rigorous analytical processes, the study endeavors to provide nuanced insights into the energy efficiency landscape of African states and pave the way for informed policy decisions and strategic interventions aimed at fostering sustainable development across the continent.

The study delved into the complex interplay between regional blocs and energy efficiency patterns across African states, employing a multi-directional efficiency analysis methodology. Through a comprehensive investigation, several key insights were gleaned:

1. The analysis revealed a diverse landscape of resource utilization practices among African states, reflecting variations in technological adoption, policy frameworks, and economic development levels across different regions. Through a multi-directional efficiency analysis, the study revealed diverse energy efficiency patterns across African states, influenced by factors such as technological advancements, renewable energy utilization, and economic development.

2. While some countries demonstrated commendable efficiency in resource utilization, others faced notable gaps and inefficiencies, indicating the need for targeted interventions and policy reforms to enhance energy efficiency and promote environmental sustainability. The evaluation of environmental energy efficiency status highlighted variations among African countries, with some exhibiting higher efficiency levels than others, indicating disparities in environmental sustainability efforts.

3. Significant opportunities for improvement in resource utilization practices were identified, offering a roadmap for implementing strategies to optimize energy consumption, reduce environmental impact, and enhance overall efficiency. Analysis of energy consumption slacks uncovered substantial energy savings potential within African states, emphasizing the need for targeted interventions to enhance energy efficiency and reduce wastage.

4. Nuanced differences in energy efficiency levels were observed across African regional blocs, highlighting the importance of collaborative efforts and policy coordination to address common environmental goals and promote sustainable development. Statistical comparisons of variable-specific efficiencies across African regional blocs demonstrated notable differences in energy efficiency levels, underscoring the varying impacts of regional integration initiatives on environmental performance.

The study underscored the critical importance of prioritizing energy efficiency and environmental sustainability in African states' development agendas. By leveraging regional cooperation, sharing best practices, and implementing targeted interventions, policymakers, regional organizations, and stakeholders can drive meaningful progress towards a more energy-efficient and environmentally sustainable future for Africa and its people.

5.3 Conclusion of the Study

The examination of the impact of regional blocs on the energy efficiency patterns of African states has yielded significant insights into the intricate dynamics of resource utilization and environmental sustainability across the continent. Through a meticulous multi-directional efficiency analysis, this study has addressed several key objectives, illuminating critical aspects of energy efficiency and regional cooperation in Africa.

Firstly, our assessment of environmental energy efficiency patterns has revealed a diverse landscape of resource utilization practices among African states. From this analysis, it is evident that there exist variations in the efficiency of energy consumption, reflecting disparities in technological adoption, policy frameworks, and economic development levels across different regions.

Secondly, the evaluation of the environmental energy efficiency status of African states has underscored both achievements and challenges in sustainable resource management. While some countries demonstrate commendable efficiency in resource utilization, others face notable gaps and inefficiencies, highlighting the need for targeted interventions and policy reforms to enhance energy efficiency and promote environmental sustainability.

Thirdly, the investigation into energy consumption slacks and savings potential has identified significant opportunities for improvement in resource utilization practices across African states. By pinpointing inefficiencies and areas of wastage, this analysis has provided a roadmap for implementing strategies to optimize energy consumption, reduce environmental impact, and enhance overall efficiency.

Lastly, the statistical comparison of variable-specific efficiencies among African regional blocs has revealed nuanced differences in energy efficiency levels across different economic and geographical groupings. While some blocs exhibit higher efficiency scores in certain variables, others face challenges that necessitate collaborative efforts and policy coordination to address common environmental goals and promote sustainable development.

In conclusion, the findings of this study emphasize the critical importance of prioritizing energy efficiency and environmental sustainability in African states' development agendas. By leveraging regional cooperation, sharing best practices, and implementing targeted interventions, policymakers, regional organizations, and stakeholders can work together to drive meaningful progress towards a more energy-efficient and environmentally sustainable future for Africa and its people.

5.4 Recommendation

For policy:

1. Governments and policymakers should prioritize the development and implementation of comprehensive energy efficiency policies tailored to the specific needs and contexts of each African state. These policies should encompass measures to incentivize investment in energy-efficient technologies, promote renewable energy sources, and enhance energy infrastructure.

2. Efforts should be made to enhance the capacity of relevant stakeholders, including government officials, industry leaders, and the general public, in understanding and implementing energy efficiency measures. This could involve educational programs, training workshops, and awareness campaigns aimed at promoting energy-saving behaviors and technologies.

3. Given the abundant renewable energy resources available in many African countries, there is a need to ramp up investment in renewable energy infrastructure. Governments should provide incentives for the development of renewable energy projects and facilitate partnerships with private sector entities and international organizations.

4. Facilitating technology transfer and innovation in energy efficiency and renewable energy sectors can play a crucial role in improving energy efficiency. Governments should foster an enabling environment for technology transfer through policies that

support research and development, innovation hubs, and collaboration with international partners.

5. African regional blocs should prioritize cooperation and collaboration on energy efficiency initiatives, sharing best practices, resources, and expertise. Regional integration efforts can also facilitate the development of cross-border energy infrastructure and the harmonization of energy policies and regulations.

For Practice:

For practitioners involved in energy management, policy development, and sustainable development initiatives in African states, the following recommendations are proposed based on the findings of this study:

1. Capacity-building initiatives should be prioritized by management to enhance technical expertise and skills in energy efficiency planning, implementation, and monitoring. Training programs, workshops, and knowledge-sharing platforms can empower stakeholders at all levels to adopt best practices and innovative solutions.
2. Management should be encouraged to adopt the energy-efficient technologies and practices can significantly reduce energy consumption and carbon emissions. Governments, businesses, and households should be incentivized to invest in energy-efficient appliances, building designs, industrial processes, and transportation systems.
3. Raising public awareness and promoting behavioral change are essential for fostering a culture of energy conservation and sustainability. Public education campaigns, outreach

activities, and community engagement initiatives can empower individuals to adopt energy-efficient behaviors and practices in their daily lives.

4. Collaboration between the public and private sectors, as well as civil society organizations, is crucial for scaling up energy efficiency initiatives. PPPs can leverage resources, expertise, and innovation to accelerate the deployment of energy-efficient solutions and infrastructure projects.
5. Improving data collection, management, and monitoring systems is essential for evidence-based decision-making and performance tracking. Governments and relevant stakeholders should invest in robust data infrastructure and information systems to assess energy efficiency outcomes and measure progress towards targets.

For further research:

1. Researchers should conduct more in-depth studies to explore specific aspects of energy efficiency dynamics in African states. This could include examining the impact of socio-economic factors, institutional frameworks, and policy interventions on energy efficiency outcomes.
2. There is a need for methodological advancements in assessing energy efficiency in African contexts. Researchers should explore innovative approaches, such as multi-directional efficiency analysis, to capture the complexities of energy efficiency patterns and dynamics.

3. The study encountered the issue of infeasibilities which it has not addressed, further study should explore to solve the infeasibility associated with multidirectional efficiency analysis

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APPENDICE

APPENDIX A

Variable Specifics Efficiency Score Across the Regional Blocs for Capital Service

Group	Country	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
AMU	Egypt	1	1	1	1	1	1	1	1	1	1	1
AMU	Mauritania	1	1	1	1	1	1	1	1	1	0.94764	1
AMU	Morocco	0.7145	0.728402	0.74275	0.7512	0.75294	0.74934	0.76006	0.75862	0.76012	0.76024	0.759599
AMU	Sudan	1	1	1	1	1	1	1	1	1	1	1
AMU	Tunisia	0.70769	0.692394	0.69133	0.71877	0.73569	0.75534	0.79536	0.93749	0.84909	1	1
EAC	Burundi	1	1	1	1	1	1	1	1	1	1	1
EAC	Djibouti	1	1	1	1	1	1	1	1	1	1	1
EAC	Kenya	1	1	1	1	1	1	1	1	1	1	1
EAC	Rwanda	1	1	1	1	1	1	1	1	1	1	1
EAC	U.R. of Tanzania: Mainland	1	1	1	1	1	1	1	1	1	1	1
ECCAS	Angola	1	1	1	1	1	1	1	1	1	0.8814	0.914466
ECCAS	Cameroon	0.80682	1	1	1	1	1	1	0.91461	0.94404	0.91341	0.896976
ECCAS	Central African Republic	1	1	1	0.7266	1	0.71896	0.7039	0.71016	0.66995	0.70325	0.597191
ECCAS	Chad	1	1	1	1	1	1	1	1	1	1	1
ECCAS	Gabon	1	1	1	1	1	1	1	1	1	1	1
ECCAS	Sao Tome and Principe	1	1	1	1	1	1	1	1	1	1	1
ECOWAS	Benin	0.6899	0.696273	0.71099	0.69404	0.72716	0.73347	0.77137	0.78957	0.8032	0.80115	0.793831
ECOWAS	Burkina Faso	0.93981	1	1	1	1	1	1	0.9883	0.99545	0.99395	0.988463
ECOWAS	Cabo Verde	1	1	1	1	1	0.92938	0.94175	0.94074	0.99954	0.92101	0.895627
ECOWAS	Côte d’Ivoire	0.78968	0.789179	0.79298	0.8414	0.8458	0.8454	0.90915	0.93027	0.96626	1	0.996128
ECOWAS	Guinea	1	1	1	1	1	1	1	1	1	1	1
ECOWAS	Niger	0.6925	1	0.72212	0.69452	0.54871	0.58521	0.66543	0.56471	0.63162	0.58469	0.57194
ECOWAS	Nigeria	1	1	1	1	1	1	1	1	1	1	1

ECOWAS	Sierra Leone	0.80544	0.845557	0.96333	0.99372	0.95126	0.99109	1	1	1	1	1
ECOWAS	Togo	0.65714	0.663296	0.6749	0.6708	0.67291	0.66439	0.69438	0.69434	0.7101	0.69539	0.712069
SADC	Botswana	1	1	1	1	1	1	1	1	1	1	1
SADC	Eswatini	0.71762	0.718968	0.73294	0.82035	1	1	1	1	1	1	1
SADC	Lesotho	0.66283	0.655213	0.67999	0.69381	0.73623	0.73271	0.75858	0.75209	0.82132	0.80119	0.818842
SADC	Mauritius	1	1	1	1	1	1	0.9135	0.94056	0.9695	1	1
SADC	Mozambique	0.76854	0.779363	0.77949	0.78777	0.81631	0.84992	0.9238	0.95636	0.98867	1	1
SADC	South Africa	0.61434	1	0.63633	1	1	1	0.67068	1	0.69016	0.68896	0.698511
SADC	Zimbabwe	0.62227	0.622327	0.61669	0.60925	0.61657	0.61761	0.62841	0.63064	0.64533	0.80688	0.83583
	GEO MEAN	0.8678	0.9009	0.8859	0.8952	0.9072	0.9003	0.9006	0.9122	0.9104	0.9129	0.911

Variable Specifics Efficiency Score Across the Regional Blocs for Capital Service

2011	2012	2013	2014	2015	2016	2017	2018	2019	Average
1	1	1	1	1	1	1	1	1	0.963
1	0.908023	1	0.877151	0.871312	1	0.807889	0.788792	0.792171	0.798
0.764614	0.759384	0.761442	0.763492	0.760164	0.758708	0.761646	0.759169	0.746285	0.98
1	1	1	1	1	1	1	1	1	0.967
1	1	1	0.928224	0.861481	0.857994	0.839347	1	1	0.965
0.885202	0.890145	0.908883	1	0.953508	0.954873	1	0.867336	0.833321	0.899
1	1	1	1	1	0.990793	0.975776	0.979391	1	0.933
1	1	1	1	1	1	1	1	1	0.762
1	1	1	1	1	1	1	1	1	0.995
1	1	0.995434	0.974416	0.96337	0.952707	1	1	1	0.935
1	1	1	1	0.824909	0.843988	1	1	0.804831	0.997
0.909612	0.915165	1	0.921056	0.909664	0.906544	0.888786	0.863114	0.870513	1

0.607925	0.6348	0.606407	0.623276	0.625569	0.635937	0.674318	1	1	0.949
1	1	1	1	1	1	1	0.945039	0.958302	1
1	1	1	1	1	1	1	1	1	0.99
1	1	1	1	1	1	1	1	1	1
0.82249	0.860153	0.865837	0.876973	0.891322	0.889462	0.87115	0.842231	0.833618	0.77
1	0.953422	0.937707	0.941387	0.925156	0.952433	0.940839	0.906694	0.869042	0.95
0.848153	0.876763	0.861504	0.823343	0.809142	0.793928	0.777005	0.78698	0.784522	0.991
1	1	1	1	1	1	1	1	1	0.754
1	1	1	1	1	0.938595	0.956841	0.959609	0.943652	0.858
0.547024	0.609819	0.642358	0.664311	0.664373	0.665857	0.682735	0.676814	0.654212	0.653
1	1	1	1	1	1	1	1	1	1
0.973394	0.995264	1	1	1	1	1	1	1	1
0.725993	0.751534	0.770148	0.775407	0.807247	0.811633	0.806667	0.806542	0.809817	1
1	1	1	1	1	0.908383	0.907655	0.907452	0.876117	0.976
1	1	0.980128	1	1	1	1	1	1	0.778
0.830959	0.839781	0.817682	0.801244	0.808567	0.818947	0.779168	0.803581	0.781613	1
1	1	1	1	1	1	1	1	1	0.729
0.993739	0.932994	0.874236	0.811442	0.807261	0.805185	0.805486	0.758815	0.719844	0.869
0.70604	0.707687	0.70798	1	0.691508	0.688102	0.687851	0.689414	0.692377	0.994
0.873557	0.926429	0.925826	0.932796	0.947636	0.953626	0.961378	0.969556	0.925255	0.783
0.9114	**0.9159**	**0.9187**	**0.9218**	**0.9026**	**0.9031**	**0.9062**	**0.9097**	**0.8959**	

Variable Specifics Efficiency Score Across the Regional Blocs for Labour

Group	Country	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
ECCAS	Angola	1	1	1	1	1	1	1	1	1	0.951989	0.996042
AMU	Egypt	1	1	1	1	1	1	1	1	1	1	1
AMU	Mauritania	1	1	1	1	1	1	1	1	1	0.973304	1
AMU	Morocco	0.762994	0.788818	0.792338	0.828554	0.809981	0.792287	0.82032	0.80789	0.811496	0.825343	0.810774
AMU	Sudan	1	1	1	1	1	1	1	1	1	1	1
AMU	Tunisia	0.859795	0.85055	0.846603	0.863106	0.877037	0.885636	0.89797	0.990106	0.923154	1	1
EAC	Burundi	1	1	1	1	1	1	1	1	1	1	1
EAC	Djibouti	1	1	1	1	1	1	1	1	1	1	1
EAC	Kenya	1	1	1	1	1	1	1	1	1	1	1
EAC	Rwanda	1	1	1	1	1	1	1	1	1	1	1
EAC	U.R. of Tanzania: Mainland	1	1	1	1	1	1	1	1	1	1	1
ECCAS	Cameroon	0.886964	1	1	1	1	1	1	0.932439	0.972664	0.920772	0.88559
ECCAS	Central African Republic	1	1	1	0.978772	1	0.992202	0.981217	0.977248	0.928357	0.937863	0.897573
ECCAS	Chad	1	1	1	1	1	1	1	1	1	1	1
ECCAS	Gabon	1	1	1	1	1	1	1	1	1	1	1
ECCAS	Sao Tome and Principe	1	1	1	1	1	1	1	1	1	1	1
ECOWAS	Benin	0.746027	0.734906	0.755011	0.713118	0.737829	0.739011	0.732039	0.741718	0.743822	0.720476	0.706035
ECOWAS	Burkina Faso	0.924458	1	1	1	1	1	1	0.982652	0.995088	0.993974	0.960519
ECOWAS	Cabo Verde	1	1	1	1	1	0.913763	0.902045	0.887021	0.999503	0.888491	0.886509
ECOWAS	Côte d'Ivoire	0.823155	0.769525	0.774818	0.842472	0.807596	0.788553	0.843131	0.906217	0.964239	1	0.993088
ECOWAS	Guinea	1	1	1	1	1	1	1	1	1	1	1
ECOWAS	Niger	0.87742	1	0.912598	0.868943	0.717044	0.801297	0.869515	0.789389	0.826221	0.741589	0.688091
ECOWAS	Nigeria	1	1	1	1	1	1	1	1	1	1	1
ECOWAS	Sierra Leone	0.808493	0.833843	0.978482	0.996606	0.961486	0.99291	1	1	1	1	1
ECOWAS	Togo	0.649834	0.668405	0.67742	0.656666	0.655557	0.645342	0.670677	0.650075	0.651947	0.630801	0.632814
SADC	Botswana	1	1	1	1	1	1	1	1	1	1	1
SADC	Eswatini	0.853943	0.88934	0.920248	0.989424	1	1	1	1	1	1	1
SADC	Lesotho	0.655185	0.644395	0.67146	0.676122	0.706732	0.699303	0.715519	0.713061	0.767113	0.757984	0.765135

SADC	Mauritius	1	1	1	1	1	1	0.967962	0.966471	0.986364	1	1
SADC	Mozambique	0.683138	0.689506	0.709232	0.708642	0.747176	0.768049	0.791695	0.804321	0.84084	1	1
SADC	South Africa	0.984435	1	0.990416	1	1	1	0.9938	1	0.989726	0.991013	0.996577
SADC	Zimbabwe	0.594318	0.59384	0.591824	0.585431	0.589383	0.584566	0.584908	0.576321	0.583321	0.6687	0.656495

Variable Specifics Efficiency Score Across the Regional Blocs for Labour

2011	2012	2013	2014	2015	2016	2017	2018	2019	Average
1	1	1	1	0.979133	0.995097	1	1	0.968819	0.995
1	1	1	1	1	1	1	1	1	0.738
1	0.964373	1	0.956947	0.969496	1	0.869243	0.8065	0.808654	0.99
0.82183	0.830351	0.845694	0.85705	0.856157	0.869868	0.894143	0.874852	0.833034	0.93
1	1	1	1	1	1	1	1	1	0.909
1	1	1	0.990784	0.934289	0.92094	0.907796	1	1	0.909
0.763208	0.694483	0.734978	1	0.791315	0.760092	1	0.728114	0.702391	0.932
1	1	1	1	1	0.955124	0.92257	0.940092	1	0.882
1	1	1	1	1	1	1	1	1	0.986
1	1	1	1	1	1	1	1	1	0.926
1	1	0.839681	0.797159	0.788834	0.792222	1	1	1	0.991
0.913295	0.921441	1	0.918196	0.951574	0.894181	0.822942	0.797384	0.82677	1
0.818531	0.809605	0.658939	0.656441	0.65855	0.679182	0.664459	1	1	0.982
1	1	1	1	1	1	1	0.853649	0.872507	1
1	1	1	1	1	1	1	1	1	0.97
1	1	1	1	1	1	1	1	1	1
0.717673	0.779008	0.78008	0.780888	0.767884	0.724317	0.730334	0.69401	0.713214	0.732
1	0.915162	0.892941	0.88278	0.799348	0.879105	0.82033	0.76561	0.794658	0.967
0.85163	0.88854	0.932721	0.851843	0.845117	0.836984	0.826878	0.834837	0.840366	0.996
1	1	1	1	1	1	1	1	1	0.827
1	1	1	1	1	0.804122	0.838688	0.894847	0.867377	0.723
0.624127	0.628311	0.645235	0.664225	0.672133	0.67232	0.686575	0.68106	0.666021	0.752
1	1	1	1	1	1	1	1	1	1

0.98213	0.996212	1	1	1	1	1	1	1	1
0.645123	0.65967	0.667861	0.67027	0.677915	0.696648	0.693773	0.725959	0.746097	1
1	1	1	1	1	0.934236	0.943215	0.979063	0.950487	0.978
1	1	0.979607	1	1	1	1	1	1	0.98
0.778118	0.789235	0.773352	0.763427	0.752624	0.761172	0.736373	0.763281	0.756074	1
1	1	1	1	1	1	1	1	1	0.669
0.795439	0.762338	0.667064	0.554472	0.566887	0.578264	0.601699	0.604946	0.593796	0.937
0.988515	0.995434	0.999899	1	0.962742	0.951176	0.933574	0.916572	0.90847	0.961
0.650557	0.733511	0.633482	0.600639	0.623226	0.608174	0.576379	0.614813	0.567913	0.611

Variable Specifics Efficiency Score Across the Regional Blocs for Energy Use

Group	Country	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
AMU	Egypt	1	1	1	1	1	1	1	1	1	1	1
AMU	Mauritania	1	1	1	1	1	1	1	1	1	0.95465	1
AMU	Morocco	0.860501	0.877128	0.875716	0.879596	0.869669	0.835345	0.849538	0.82262	0.8162	0.815568	0.819281
AMU	Sudan	1	1	1	1	1	1	1	1	1	1	1
AMU	Tunisia	0.863831	0.851898	0.850445	0.887944	0.917402	0.904103	0.942269	0.993838	0.955741	1	1
EAC	Burundi	1	1	1	1	1	1	1	1	1	1	1
EAC	Djibouti	1	1	1	1	1	1	1	1	1	1	1
EAC	Kenya	1	1	1	1	1	1	1	1	1	1	1
EAC	Rwanda	1	1	1	1	1	1	1	1	1	1	1
EAC	U.R. of Tanzania: Mainland	1	1	1	1	1	1	1	1	1	1	1
ECCAS	Angola	1	1	1	1	1	1	1	1	1	0.892731	0.979523
ECCAS	Cameroon	0.901965	1	1	1	1	1	1	0.933423	0.951521	0.904609	0.857432
ECCAS	Central African Republic	1	1	1	0.952808	1	0.800819	0.855718	0.839736	0.803792	0.822186	0.811168
ECCAS	Chad	1	1	1	1	1	1	1	1	1	1	1

ECCAS	Gabon	1	1	1	1	1	1	1	1	1	1	1
ECCAS	Sao Tome and Principe	1	1	1	1	1	1	1	1	1	1	1
ECOWAS	Benin	0.850985	0.853531	0.863061	0.811586	0.777752	0.759909	0.764258	0.763514	0.774853	0.72445	0.694187
ECOWAS	Burkina Faso	0.965922	1	1	1	1	1	1	0.957364	0.990131	0.979136	0.929315
ECOWAS	Cabo Verde	1	1	1	1	1	0.86861	0.888758	0.871912	0.921528	0.884231	0.876731
ECOWAS	Côte d’Ivoire	0.816482	0.814218	0.828642	0.846276	0.845122	0.824667	0.894401	0.898434	0.933682	1	0.961494
ECOWAS	Guinea	1	1	1	1	1	1	1	1	1	1	1
ECOWAS	Niger	0.910959	1	0.94538	0.909144	0.613013	0.648862	0.879356	0.626559	0.68414	0.609448	0.574002
ECOWAS	Nigeria	1	1	1	1	1	1	1	1	1	1	1
ECOWAS	Sierra Leone	0.842975	0.848998	0.970583	0.993484	0.872642	0.974495	1	1	1	1	1
ECOWAS	Togo	0.73871	0.755074	0.739937	0.707485	0.670722	0.664578	0.696226	0.67065	0.665405	0.625555	0.630053
SADC	Botswana	1	1	1	1	1	1	1	1	1	1	1
SADC	Eswatini	0.816841	0.826287	0.838327	0.888021	1	1	1	1	1	1	1
SADC	Lesotho	0.784043	0.792965	0.799521	0.806642	0.806377	0.76632	0.777039	0.745856	0.831551	0.786426	0.797292
SADC	Mauritius	1	1	1	1	1	1	0.898138	0.892252	0.919606	1	1
SADC	Mozambique	0.639758	0.63691	0.648578	0.645592	0.648815	0.669161	0.678169	0.702615	0.728574	1	1
SADC	South Africa	0.669812	1	0.683483	1	1	1	0.716938	1	0.710613	0.710514	0.711832
SADC	Zimbabwe	0.608099	0.612701	0.606209	0.595883	0.588336	0.57528	0.573755	0.557408	0.566528	0.658067	0.649809

Variable Specifics Efficiency Score Across the Regional Blocs for Energy Use

Group	Country	2011	2012	2013	2014	2015	2016	2017	2018	2019	Average
AMU	Egypt	1	1	1	1	1	1	1	1	1	1
AMU	Mauritania	1	0.976229	1	0.978822	0.987122	1	0.913233	0.877673	0.874342	0.978104
AMU	Morocco	0.848908	0.851975	0.878509	0.893062	0.902387	0.929202	0.947666	0.944869	0.929278	0.872351
AMU	Sudan	1	1	1	1	1	1	1	1	1	1
AMU	Tunisia	1	1	1	0.995279	0.970027	0.970965	0.962146	1	1	0.953294
EAC	Burundi	0.820517	0.791899	0.801943	1	0.809966	0.787301	1	0.88076	0.870621	0.93815
EAC	Djibouti	1	1	1	1	1	0.966745	0.954281	0.94593	1	0.993348
EAC	Kenya	1	1	1	1	1	1	1	1	1	1
EAC	Rwanda	1	1	1	1	1	1	1	1	1	1
EAC	U.R. of Tanzania: Mainland	1	1	0.992988	0.967529	0.978794	0.955525	1	1	1	0.994742
ECCAS	Angola	1	1	1	1	0.986213	0.997184	1	1	0.992637	0.992414
ECCAS	Cameroon	0.857759	0.84789	1	0.888674	0.89922	0.930648	0.91511	0.917957	0.93384	0.937002
ECCAS	Central African Republic	0.688666	0.687466	0.677761	0.676481	0.673633	0.680807	0.80903	1	1	0.839004
ECCAS	Chad	1	1	1	1	1	1	1	0.883726	0.920722	0.990222
ECCAS	Gabon	1	1	1	1	1	1	1	1	1	1
ECCAS	Sao Tome and Principe	1	1	1	1	1	1	1	1	1	1
ECOWAS	Benin	0.718211	0.750456	0.790526	0.809752	0.805233	0.796715	0.807365	0.778953	0.817281	0.785629
ECOWAS	Burkina Faso	1	0.809925	0.87951	0.872341	0.778719	0.863744	0.883526	0.861468	0.862641	0.931687
ECOWAS	Cabo Verde	0.821997	0.846767	0.848045	0.820963	0.818277	0.807803	0.810548	0.799468	0.828418	0.885703
ECOWAS	Côte d’Ivoire	1	1	1	1	1	1	1	1	1	0.933171
ECOWAS	Guinea	1	1	1	1	1	0.816235	0.866796	0.914042	0.913695	0.975538
ECOWAS	Niger	0.548823	0.576577	0.595089	0.614436	0.601234	0.592728	0.740961	0.780878	0.786741	0.711917
ECOWAS	Nigeria	1	1	1	1	1	1	1	1	1	1
ECOWAS	Sierra Leone	0.933129	0.98603	1	1	1	1	1	1	1	0.971117

ECOWAS	Togo	0.644709	0.660404	0.666456	0.663008	0.66495	0.712097	0.750117	0.782101	0.811641	0.695994
SADC	Botswana	1	1	1	1	1	0.965453	0.976627	0.99194	0.980116	0.995707
SADC	Eswatini	1	1	0.990378	1	1	1	1	1	1	0.967993
SADC	Lesotho	0.84346	0.841424	0.858239	0.856993	0.854605	0.869194	0.812722	0.851603	0.849738	0.816601
SADC	Mauritius	1	1	1	1	1	1	1	1	1	0.9855
SADC	Mozambique	0.691709	0.639489	0.610904	0.547379	0.561857	0.581041	0.620146	0.637554	0.6276	0.675793
SADC	South Africa	0.722893	0.731303	0.729721	1	0.716346	0.711018	0.709883	0.709216	0.692438	0.796301
SADC	Zimbabwe	0.654235	0.714401	0.68425	0.657856	0.677511	0.745237	0.812596	0.828893	0.691199	0.652913

Variable Specifics Efficiency Score Across the Regional Blocs for GDP

Group	Country	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	20
AMU	Egypt	1	1	1	1	1	1	1	1	1	1	
AMU	Mauritania	1	1	1	1	1	1	1	1	1	0.989532	
AMU	Morocco	0.891222	0.913913	0.913047	0.923203	0.914152	0.891542	0.904362	0.888414	0.888045	0.8948	0.8895
AMU	Sudan	1	1	1	1	1	1	1	1	1	1	
AMU	Tunisia	0.924491	0.877082	0.873648	0.920087	0.93984	0.945791	0.962968	0.99654	0.97247	1	
EAC	Burundi	1	1	1	1	1	1	1	1	1	1	
EAC	Djibouti	1	1	1	1	1	1	1	1	1	1	
EAC	Kenya	1	1	1	1	1	1	1	1	1	1	
EAC	Rwanda	1	1	1	1	1	1	1	1	1	1	
EAC	U.R. of Tanzania: Mainland	1	1	1	1	1	1	1	1	1	1	
ECCAS	Angola	1	1	1	1	1	1	1	1	1	0.963887	0.998
ECCAS	Cameroon	0.981776	1	1	1	1	1	1	0.970624	0.986914	0.971072	0.948
ECCAS	Central African Republic	1	1	1	0.989923	1	0.996221	0.991973	0.990592	0.955585	0.970201	0.9662
ECCAS	Chad	1	1	1	1	1	1	1	1	1	1	
ECCAS	Gabon	1	1	1	1	1	1	1	1	1	1	
ECCAS	Sao Tome and Principe	1	1	1	1	1	1	1	1	1	1	

ECOWAS	Benin	0.865036	0.864675	0.883566	0.827178	0.834133	0.816771	0.847761	0.862023	0.870992	0.829291	0.8012
ECOWAS	Burkina Faso	0.982045	1	1	1	1	1	1	0.99527	0.998638	0.998121	0.9936
ECOWAS	Cabo Verde	1	1	1	1	1	0.961384	0.966224	0.966757	0.999902	0.962694	0.9518
ECOWAS	Côte d’Ivoire	0.868803	0.837058	0.839788	0.908724	0.898155	0.894396	0.949964	0.969779	0.989049	1	0.9985
ECOWAS	Guinea	1	1	1	1	1	1	1	1	1	1	
ECOWAS	Niger	0.977031	1	0.992923	0.969785	0.915679	0.968939	0.989991	0.970799	0.949859	0.884	0.833
ECOWAS	Nigeria	1	1	1	1	1	1	1	1	1	1	
ECOWAS	Sierra Leone	0.893349	0.906044	0.989117	0.998445	0.976758	0.996222	1	1	1	1	
ECOWAS	Togo	0.736009	0.76519	0.762805	0.716589	0.707919	0.66365	0.724197	0.683972	0.686855	0.60968	0.6256
SADC	Botswana	1	1	1	1	1	1	1	1	1	1	
SADC	Eswatini	0.935024	0.953894	0.969893	0.996133	1	1	1	1	1	1	
SADC	Lesotho	0.763986	0.769024	0.793368	0.800751	0.825301	0.787887	0.808951	0.780459	0.892505	0.86359	0.87
SADC	Mauritius	1	1	1	1	1	1	0.978326	0.981376	0.992246	1	
SADC	Mozambique	0.868617	0.877663	0.890352	0.879315	0.908518	0.93526	0.964318	0.978055	0.994265	1	
SADC	South Africa	0.984476	1	0.99047	1	1	1	0.993818	1	0.989692	0.99099	0.996
SADC	Zimbabwe	0.470423	0.477211	0.466818	0.45527	0.4893	0.479131	0.49257	0.50354	0.54556	0.81213	0.8320

Variable Specifics Efficiency Score Across the Regional Blocs for GDP

Group	Country	2011	2012	2013	2014	2015	2016	2017	2018	2019	AVG
AMU	Egypt	1	1	0.997548	0.98708	0.988353	0.977805	1	1	1	0.997539
AMU	Mauritania	1	1	1	1	1	1	1	1	1	1
AMU	Morocco	1	0.989356	1	0.985913	0.990569	1	0.934433	0.888033	0.890591	0.983421
AMU	Sudan	0.908304	0.910177	0.925423	0.932438	0.936362	0.951182	0.963618	0.96006	0.944783	0.917231
AMU	Tunisia	1	1	1	1	1	1	1	1	1	1
EAC	Burundi	1	1	1	0.997068	0.980046	0.979392	0.972261	1	1	0.967084
EAC	Djibouti	0.877202	0.933204	0.970084	1	0.988866	0.958561	1	0.905572	0.880393	0.975694
EAC	Kenya	1	1	1	1	1	0.991448	0.982352	0.986303	1	0.998005
EAC	Rwanda	1	1	1	1	1	1	1	1	1	1
EAC	U.R. of Tanzania:	1	1	1	1	1	1	1	1	1	1

	Mainland										
ECCAS	Angola	1	1	1	1	0.991258	0.998213	1	1	0.994121	0.997276
ECCAS	Cameroon	0.967142	0.966721	1	0.976712	0.983834	0.969945	0.944273	0.939154	0.948714	0.977755
ECCAS	Central African Republic	0.976329	0.986731	0.826789	0.806037	0.813966	0.858069	0.684256	1	1	0.940644
ECCAS	Chad	1	1	1	1	1	1	1	0.960071	0.976152	0.996811
ECCAS	Gabon	1	1	1	1	1	1	1	1	1	1
ECCAS	Sao Tome and Principe	1	1	1	1	1	1	1	1	1	1
ECOWAS	Benin	0.840351	0.882003	0.879863	0.883555	0.9028	0.890402	0.885227	0.841557	0.853432	0.858094
ECOWAS	Burkina Faso	1	0.972379	0.969401	0.968255	0.934961	0.967399	0.955586	0.929007	0.918256	0.979149
ECOWAS	Cabo Verde	0.904178	0.961223	0.971759	0.880653	0.888234	0.909454	0.820856	0.831876	0.83933	0.940819
ECOWAS	Côte d’Ivoire	1	1	1	1	1	1	1	1	1	0.957714
ECOWAS	Guinea	1	1	1	1	1	0.946524	0.965572	0.972128	0.966943	0.992558
ECOWAS	Niger	0.747293	0.711052	0.745478	0.766151	0.785741	0.813904	0.822357	0.859889	0.845334	0.877509
ECOWAS	Nigeria	1	1	1	1	1	1	1	1	1	1
ECOWAS	Sierra Leone	0.990078	0.998053	1	1	1	1	1	1	1	0.987403
ECOWAS	Togo	0.674901	0.711935	0.726701	0.726151	0.762988	0.800497	0.79925	0.838313	0.862615	0.729293
SADC	Botswana	1	1	1	1	1	0.982534	0.987089	0.995807	0.989272	0.997735
SADC	Eswatini	1	1	0.994331	1	1	1	1	1	1	0.992464
SADC	Lesotho	0.897601	0.899845	0.892644	0.885883	0.877473	0.895528	0.810425	0.87628	0.865827	0.843151
SADC	Mauritius	1	1	1	1	1	1	1	1	1	0.997597
SADC	Mozambique	0.995802	0.949194	0.885988	0.790832	0.788539	0.77905	0.788532	0.733512	0.670566	0.883919
SADC	South Africa	0.988473	0.99545	0.9999	1	0.961554	0.948944	0.929044	0.909235	0.899532	0.978908
SADC	Zimbabwe	0.876823	0.931892	0.929661	0.934919	0.947177	0.952128	0.960858	0.970121	0.925523	0.722657

Variable Specifics Efficiency Score Across the Regional Blocs for CO2

Group	Country	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	20
AMU	Egypt	1	1	1	1	1	1	1	1	1	1	

AMU	Mauritania	1	1	1	1	1	1	1	1	1	0.980554	
AMU	Morocco	0.832252	0.807822	0.820888	0.842397	0.845701	0.825641	0.837167	0.838782	0.838807	0.83379	0.8422
AMU	Sudan	1	1	1	1	1	1	1	1	1	1	
AMU	Tunisia	0.905933	0.858815	0.856689	0.902305	0.913362	0.928654	0.940359	0.956905	0.950826	1	
EAC	Burundi	1	1	1	1	1	1	1	1	1	1	
EAC	Djibouti	1	1	1	1	1	1	1	1	1	1	
EAC	Kenya	1	1	1	1	1	1	1	1	1	1	
EAC	Rwanda	1	1	1	1	1	1	1	1	1	1	
EAC	U.R. of Tanzania: Mainland	1	1	1	1	1	1	1	1	1	1	
ECCAS	Angola	1	1	1	1	1	1	1	1	1	0.898376	0.9951
ECCAS	Cameroon	0.980141	1	1	1	1	1	1	0.942884	0.973935	0.951296	0.9229
ECCAS	Central African Republic	1	1	1	0.9843	1	0.99412	0.989201	0.987688	0.951584	0.966815	0.9770
ECCAS	Chad	1	1	1	1	1	1	1	1	1	1	
ECCAS	Gabon	1	1	1	1	1	1	1	1	1	1	
ECCAS	Sao Tome and Principe	1	1	1	1	1	1	1	1	1	1	
ECOWAS	Benin	0.833481	0.808617	0.804215	0.773591	0.798751	0.795027	0.767357	0.772786	0.782457	0.763505	0.7341
ECOWAS	Burkina Faso	0.973207	1	1	1	1	1	1	0.977897	0.989317	0.987139	0.9525
ECOWAS	Cabo Verde	1	1	1	1	1	0.93792	0.941314	0.953419	0.999852	0.949519	0.9264
ECOWAS	Côte d'Ivoire	0.817364	0.798589	0.81361	0.880784	0.845234	0.828316	0.880548	0.925584	0.972116	1	0.9959
ECOWAS	Guinea	1	1	1	1	1	1	1	1	1	1	
ECOWAS	Niger	0.968753	1	0.989386	0.947417	0.900716	0.959542	0.98474	0.955313	0.914034	0.81458	0.7620
ECOWAS	Nigeria	1	1	1	1	1	1	1	1	1	1	
ECOWAS	Sierra Leone	0.874289	0.865051	0.935506	0.991904	0.93846	0.988764	1	1	1	1	
ECOWAS	Togo	0.730823	0.741502	0.746336	0.722665	0.727569	0.708764	0.736025	0.705422	0.68685	0.642454	0.6522
SADC	Botswana	1	1	1	1	1	1	1	1	1	1	
SADC	Eswatini	0.912305	0.938687	0.960513	0.994374	1	1	1	1	1	1	
SADC	Lesotho	0.653201	0.638745	0.664168	0.668204	0.702618	0.689268	0.702766	0.70591	0.761161	0.75123	0.759
SADC	Mauritius	1	1	1	1	1	1	0.967649	0.96922	0.987184	1	
SADC	Mozambique	0.81371	0.809886	0.818056	0.789893	0.811228	0.829884	0.859882	0.875701	0.944114	1	

SADC	South Africa	0.645764	1	0.63954	1	1	1	0.655616	1	0.647544	0.642519	0.6473
SADC	Zimbabwe	0.60028	0.607753	0.605652	0.600683	0.612369	0.59595	0.594304	0.586465	0.594112	0.732319	0.6984

Variable Specifics Efficiency Score Across the Regional Blocs for CO2

Group	Country	2011	2012	2013	2014	2015	2016	2017	2018	2019	Average
AMU	Angola	1	1	0.955405	0.929268	0.92119	0.943294	1	1	1	0.987458
AMU	Mauritania	1	1	1	1	1	1	1	1	1	1
AMU	Morocco	1	0.972211	1	0.909194	0.931597	1	0.828607	0.740312	0.748341	0.955541
AMU	Sudan	0.857986	0.84662	0.853253	0.857838	0.873816	0.884886	0.865672	0.8136	0.797675	0.840844
AMU	Tunisia	1	1	1	1	1	1	1	1	1	1
EAC	Burundi	1	1	1	0.944052	0.912519	0.919779	0.884939	1	1	0.943757
EAC	Djibouti	0.917474	0.951231	0.976953	1	0.989321	0.945223	1	0.886918	0.869022	0.976807
EAC	Kenya	1	1	1	1	1	0.968114	0.796164	0.941058	1	0.985267
EAC	Rwanda	1	1	1	1	1	1	1	1	1	1
EAC	U.R. of Tanzania: Mainland	1	1	1	1	1	1	1	1	1	1
ECCAS	Egypt	1	1	1	1	0.935351	0.943005	1	1	0.953531	0.986268
ECCAS	Cameroon	0.949159	0.945859	1	0.967652	0.975233	0.956442	0.674086	0.839701	0.897638	0.948851
ECCAS	Central African Republic	0.98357	0.990974	0.897414	0.883543	0.888659	0.913418	0.741304	1	1	0.957483
ECCAS	Chad	1	1	1	1	1	1	1	0.795048	0.826342	0.98107
ECCAS	Gabon	1	1	1	1	1	1	1	1	1	1
ECCAS	Sao Tome and Principe	1	1	1	1	1	1	1	1	1	1
ECOWAS	Benin	0.743956	0.771283	0.781305	0.788329	0.791249	0.778646	0.662586	0.677198	0.693727	0.766111
ECOWAS	Burkina Faso	1	0.860851	0.873145	0.878313	0.845972	0.861985	0.672306	0.753809	0.755348	0.919093
ECOWAS	Cabo Verde	0.892794	0.954361	0.961063	0.892385	0.900138	0.904356	0.724555	0.739347	0.745176	0.921133
ECOWAS	Côte d'Ivoire	1	1	1	1	1	1	1	1	1	0.937906

ECOWAS	Guinea	1	1	1	1	1	0.842257	0.761309	0.849929	0.859748	0.965662
ECOWAS	Niger	0.719873	0.711603	0.739527	0.743931	0.744376	0.753445	0.626603	0.785338	0.752611	0.838691
ECOWAS	Nigeria	1	1	1	1	1	1	1	1	1	1
ECOWAS	Sierra Leone	0.92514	0.939681	1	1	1	1	1	1	1	0.97294
ECOWAS	Togo	0.672448	0.691316	0.701387	0.707125	0.711623	0.731672	0.668118	0.670061	0.689574	0.702201
SADC	Botswana	1	1	1	1	1	0.970352	0.945601	0.915608	0.898659	0.986511
SADC	Eswatini	1	1	0.991769	1	1	1	1	1	1	0.989882
SADC	Lesotho	0.762552	0.761957	0.752144	0.732306	0.733491	0.744714	0.702421	0.787637	0.780073	0.722694
SADC	Mauritius	1	1	1	1	1	1	1	1	1	0.996203
SADC	Mozambique	0.9186	0.795393	0.735225	0.61208	0.666248	0.662771	0.593381	0.621781	0.610408	0.788412
SADC	South Africa	0.656797	0.663887	0.662587	1	0.658191	0.655961	0.661512	0.653715	0.64432	0.756767
SADC	Zimbabwe	0.67704	0.774603	0.686686	0.660284	0.679145	0.719977	0.754207	0.75642	0.664004	0.660034

APPENDIX B

R Commands for MEA Efficiency

ee=read.delim("clipboard")

require(Benchmarking)

x1=cbind(ee$Labour[1:32],ee$Energy[1:32],ee$Capital[1:32],ee$C02[1:32] #column bind vectors x into matrix x in year 1 matrix

x2=cbind(ee$Labour[33:64],ee$Energy[33:64],ee$Capital[33:64],ee$C02[33:64], #column bind vectors x into matrix x in year 2 matrix

y1=cbind(ee$GDP[1:32]) #column bind vectors y into matrix y in year 1 matrix

y2=cbind(ee$GDP[33:64]) #column bind vectors y into matrix x in year 2 matrix

options(max.print=999999)

##MEA Inefficiency under CRS##

mc1=mea(x1,y1,RTS = "crs",ORIENTATION = "in-out",XREF = x1,YREF = y1)#own period mea ineff score in yr 1

mc2=mea(x2,y2,RTS = "crs",ORIENTATION = "in-out",XREF = x2,YREF = y2)#own period beta value in yr 2

mc12=mea(x1,y1,RTS = "crs",ORIENTATION = "in-out",XREF = x2,YREF = y2)#cross period mea ineff score in yr 1

mc21=mea(x2,y2,RTS = "crs",ORIENTATION = "in-out",XREF = x1,YREF = y1)#cross period mea ineffi score in yr 2

round(data.frame(mc1$eff,mc12$eff,mc2$eff,mc21$eff),2) #yr 1 results

round(data.frame(mc2$eff,mc21$eff),2) #yr 2 results

##MEA Inefficiency under CRS##

mv1=mea(x1,y1,RTS = "vrs",ORIENTATION = "in-out",XREF = x1,YREF = y1)#own period mv2=mea(x2,y2,RTS = "vrs",ORIENTATION = "in-out",XREF = x2,YREF = y2)#own period

mv12=mea(x1,y1,RTS = "vrs",ORIENTATION = "in-out",XREF = x2,YREF = y2)#cross period

mv21=mea(x2,y2,RTS = "vrs",ORIENTATION = "in-out",XREF = x1,YREF = y1)#cross period

round(data.frame(mv1$eff,mv12$eff),2) #yr 1 results, beta value, MEA technical ineff score

round(data.frame(mv2$eff,mv21$eff),2) #yr 2 results, beta value, MEA technical ineff score

mv1$lambda #weight/lambdas of peers for each firm used to get MEA benchmark or PIP

eimv=mv1$eff * mv1$direct # MEA potential saving in inputs, excess inputs, in yr 1

eiev=(1-ev$eff) * x # Farrell potential saving in inputs, excess inputs

##Distances to IRP, CRS##

mc1$direct # gives distance (diagonal) which to travel to the ideal point and also gives the vertical& horizontal distance to the DEA benchmark

mc2$direct

mc12$direct

mc21$direct

##Distances to IRP, VRS##

mv1$direct # gives distance (diagonal) which to travel to the ideal point and also gives the vertical& horizontal distance to the DEA benchmark

mv2$direct

mv12$direct

mv21$direct

######CRS: Input excesses & output shortfalls###

ecL1c=mc1$direct[,-(2:6)] #removes 2nd to 6th column & cal excess input in yr 1 rel to F1 to add to actual input to get IRP

ecE1c=mc1$direct[,-(3:6)][,-1]

ecK1c=mc1$direct[,-(4:6)][,-(1:2)]

ecG1c=mc1$direct[,-(5:6)][,-(1:3)]

ecC1c=mc1$direct[,-(6)][,-(1:4)]

ecL2c=mc2$direct[,-(2:6)] #removes 2nd to 6th column & cal excess input in yr 2 rel to F2 to add to actual input to get IRP

ecE2c=mc2$direct[,-(3:6)][,-1]

ecK2c=mc2$direct[,-(4:6)][,-(1:2)]

ecG2c=mc2$direct[,-(5:6)][,-(1:3)]

ecC2c=mc2$direct[,-(6)][,-(1:4)]

ecL12c=mc12$direct[,-(2:6)] #removes 2nd to 6th column & cal excess input in yr 1 rel to F2 to add to actual input to get IRP

ecE12c=mc12$direct[,-(3:6)][,-1]

ecK12c=mc12$direct[,-(4:6)][,-(1:2)]

ecG12c=mc12$direct[,-(5:6)][,-(1:3)]

ecC12c=mc12$direct[,-(6)][,-(1:4)]

ecL21c=mc21$direct[,-(2:6)] #removes 2nd to 6th column & cal excess input in yr 2 rel to F1 to add to actual input to get IRP

ecE21c=mc21$direct[,-(3:6)][,-1]

ecK21c=mc21$direct[,-(4:6)][,-(1:2)]

ecG21c=mc21$direct[,-(5:6)][,-(1:3)]

ecC21c=mc21$direct[,-(6)][,-(1:4)]

######VRS: Input excesses & output shortfalls###

ecL1v=mv1$direct[,-(2:6)] #removes 2nd to 6th column & cal excess input in yr 1 rel to F1 to add to actual input to get IRP

ecE1v=mv1$direct[,-(3:6)][,-1]

ecK1v=mv1$direct[,-(4:6)][,-(1:2)]

ecG1v=mv1$direct[,-(5:6)][,-(1:3)]

ecC1v=mv1$direct[,-(6)][,-(1:4)]

ecL2v=mv2$direct[,-(2:6)] #removes 2nd to 6th column & cal excess input in yr 2 rel to F2 to add to actual input to get IRP

ecE2v=mv2$direct[,-(3:6)][,-1]

ecK2v=mv2$direct[,-(4:6)][,-(1:2)]

ecG2v=mv2$direct[,-(5:6)][,-(1:3)]

ecC2v=mv2$direct[,-(6)][,-(1:4)]

ecL12v=mv12$direct[,-(2:6)] #removes 2nd to 6th column & cal excess input in yr 1 rel to F2 to add to actual input to get IRP

ecE12v=mv12$direct[,-(3:6)][,-1]

ecK12v=mv12$direct[,-(4:6)][,-(1:2)]

ecG12v=mv12$direct[,-(5:6)][,-(1:3)]

ecC12v=mv12$direct[,-(6)][,-(1:4)]

ecL21v=mv21$direct[,-(2:6)] #removes 2nd to 6th column & cal excess input in yr 2 rel to F1 to add to actual input to get IRP

ecE21v=mv21$direct[,-(3:6)][,-1]

ecK21v=mv21$direct[,-(4:6)][,-(1:2)]

ecG21v=mv21$direct[,-(5:6)][,-(1:3)]

```
ecC21v=mv21$direct[,-(6)][,-(1:4)]
```

#STEP 1; Identify ideal reference point & solve LPP for it, 1 for each input and/or output dimension, CRS

```
#IRPx=(k$x-ecx) #IRP for x: x=actual input,  ecx=input excess

#IRPy=(k$y+ecy) #IRP for y: y=actual output, ecy=output shortfall

#input excess & output shortfall are found in the me$direct depending on orientation, UNDER CRS

IRPL11c=(ee$Labour[1:32]-ecL1c) #IRP for x in yr1 rel to F1

IRPE11c=(ee$Energy[1:32]-ecE1c)

IRPK11c=(ee$Capital[1:32]-ecK1c)

IRPG11c=(ee$GDP[1:32]+ecG1c) #IRP for y in yr1 rel to F1

IRPC11c=(ee$C02[1:32]-ecC1c)

IRPL22c=(ee$Labour[33:64]-ecL2c) #IRP for x in yr2 rel to F2

IRPE22c=(ee$Energy[32:64]-ecE2c)

IRPK22c=(ee$Capital[33:64]-ecK2c)

IRPG22c=(ee$GDP[33:64]+ecG2c) #IRP for y in yr2 rel to F2

IRPC22c=(ee$C02[33:64]-ecC2c)

IRPL12c=(ee$Labour[1:32]-ecL12c) #IRP for x in cross yr1 rel to F2

IRPE12c=(ee$Energy[1:32]-ecE12c)

IRPK12c=(ee$Capital[1:32]-ecK12c)

IRPG12c=(ee$GDP[1:32]+ecG12c) #IRP for y in cross yr1 rel to F2

IRPC12c=(ee$C02[1:32]-ecC12c)

IRPL21c=(ee$Labour[33:64]-ecL21c)#IRP for x in cross yr2 rel to F1
```

```
IRPE21c=(ee$Energy[33:64]-ecE21c)

IRPK21c=(ee$Capital[33:64]-ecK21c)

IRPG21c=(ee$GDP[33:64]+ecG21c)#IRP for y in cross yr2 rel to F1

IRPC21c=(ee$C02[33:64]-ecC21c)
```

Identify ideal reference point & solve LPP for it, 1 for each input and/or output dimension, VRS##

```
IRPL11v=(ee$Labour[1:32]-ecL1v) #IRP for x in yr1 rel to F1

IRPE11v=(ee$Energy[1:32]-ecE1v)

IRPK11v=(ee$Capital[1:32]-ecK1v)

IRPG11v=(ee$GDP[1:32]+ecG1v) #IRP for y in yr1 rel to F1

IRPC11v=(ee$C02[1:32]-ecC1v)

IRPL22v=(ee$Labour[33:64]-ecL2v) #IRP for x in yr2 rel to F2

IRPE22v=(ee$Energy[33:64]-ecE2v)

IRPK22v=(ee$Capital[33:64]-ecK2v)

IRPG22v=(ee$GDP[33:64]+ecG2v) #IRP for y in yr2 rel to F2

IRPC22v=(ee$C02[33:64]-ecC2v)

IRPL12v=(ee$Labour[1:32]-ecL12v) #IRP for x in cross yr1 rel to F2

IRPE12v=(ee$Energy[1:32]-ecE12v)

IRPK12v=(ee$Capital[1:32]-ecK12v)

IRPG12v=(ee$GDP[1:32]+ecG12v) #IRP for y in cross yr1 rel to F2

IRPC12v=(ee$C02[1:32]-ecC12v)

IRPL21v=(ee$Labour[33:64]-ecL21v)#IRP for x in cross yr2 rel to F1

IRPE21v=(ee$Ene$[33:64]-ecE21v)
```

IRPK21v=(ee$Capital[33:64]-ecK21v)

IRPG21v=(ee$GDP[33:64]+ecG21v)#IRP for y in cross yr2 rel to F1

IRPC21v=(ee$C02[33:64]-ecC21v)

#STEP 2; Find PIP or MEA Benchmark(MB) using IRP by moving input/output from IRP to target point(MB)

#PIPx = Xi0 - mc$eff(Xi0-IRPx), d*=IRPx, beta=MEA input INEFF or mv$eff, Xi0=observed input

#PIPy = Yi0 + beta(xi0-d*), d*=IRPy, beta=MEA output INEFF or mv$eff, Yi0=observed output

#PIP=yi0 + beta(\delta*-yi0) \delta*=IRP, yi0= output, beta=mea inefficiency

######## CRS PIP #########

PIPL11c=ee$Labour[1:32]-mc1$eff*(ee$Labour[1:32]-IRPL11c) #PIP or MB for input x in yr1 rel to F1

PIPE11c=ee$Energy[1:32]-mc1$eff*(ee$Energy[1:32]-IRPE11c)

PIPK11c=ee$Capital[1:32]-mc1$eff*(ee$Capital[1:32]-IRPK11c)

PIPG11c=ee$GDP[1:32]+mc1$eff*(IRPG11c-k$GDP[1:32])#PIP or MB for output y in yr1 rel to F1

PIPC11c=ee$C02[1:32]-mc1$eff*(ee$C02[1:32]-IRPC11c)

PIPL22c=ee$Labour[33:64]-mc2$eff*(ee$Labour[33:64]-IRPL22c) #PIP or MB for input x in yr2 rel to F2

PIPE22c=ee$Energy[33:64]-mc2$eff*(ee$Energy[33:64]-IRPE22c)

PIPK22c=ee$Capital[33:64]-mc2$eff*(ee$Capital[33:64]-IRPK22c)

PIPG22c=ee$GDP[33:64]+mc2$eff*(IRPG22c-ee$GDP[33:64])#PIP or MB for output y in yr2 rel to F2

PIPC22c=ee$C02[33:64]-mc2$eff*(ee$C02[33:64]-IRPC22c)

PIPL12c=ee$Labour[1:32]-mc12$eff*(ee$Labour[1:32]-IRPL12c) ##PIP or MB for input x in yr1 rel to F2

PIPE12c=ee$Energy[1:32]-mc12$eff*(ee$Energy[1:32]-IRPE12c)

PIPK12c=ee$Capital[1:32]-mc12$eff*(ee$Capital[1:32]-IRPK12c)

PIPG12c=ee$GDP[1:32]+mc12$eff*(IRPG12c-e$GDP[1:32])#PIP or MB for output y in yr1 rel to F2

PIPC12c=ee$C02[1:32]-mc12$eff*(ee$C02[1:32]-IRPC12c)

PIPL21c=ee$Labour[33:64]-mc21$eff*(ee$Labour[33:64]-IRPL21c)#PIP or MB for input x in yr2 rel to F1

PIPE21c=ee$Energy[33:64]-mc21$eff*(ee$Energy[33:64]-IRPE21c)

PIPK21c=ee$Capital[33:64]-mc21$eff*(ee$Capital[33:64]-IRPK21c)

PIPG21c=ee$GDP[33:64]+mc21$eff*(IRPG21c-ee$GDP[33:64])#PIP or MB for output y in yr2 rel to F1

PIPC21c=ee$C02[33:64]-mc21$eff*(ee$C02[33:64]-IRPC21c)

round(data.frame(PIPL12c,PIPE12c,PIPK12c,PIPG12c,PIPC12c,PIPM12c,PIPL21c,PIPE21c,PIPK21c,PIPG21c,PIPC21c,PIPM21c),2)

######## **VRS PIP** #########

PIPL11v=ee$Labour[1:32]-mv1$eff*(ee$Labour[1:32]-IRPL11v) #PIP or MB for input x in yr1 rel to F1

PIPE11v=ee$Energy[1:32]-mv1$eff*(ee$Energy[1:32]-IRPE11v)

PIPK11v=ee$Capital[1:32]-mv1$eff*(ee$Capital[1:32]-IRPK11v)

PIPG11v=ee$GDP[1:32]+mv1$eff*(IRPG11v-ee$GDP[1:32])#PIP or MB for output y in yr1 rel to F1

PIPC11v=ee$C02[1:32]-mv1$eff*(ee$C02[1:32]-IRPC11v)

```
PIPL22v=ee$Labour[33:64]-mv2$eff*(ee$Labour[33:64]-IRPL22v) #PIP or MB for input x in yr2 rel to F2
PIPE22v=ee$Energy[33:64]-mv2$eff*(ee$Energy[33:64]-IRPE22v)
PIPK22v=ee$Capital[33:64]-mv2$eff*(ee$Capital[33:64]-IRPK22v)
PIPG22v=ee$GDP[33:64]+mv2$eff*(IRPG22v-ee$GDP[33:64])#PIP or MB for output y in yr2 rel to F2
PIPC22v=ee$C02[33:64]-mv2$eff*(ee$C02[33:64]-IRPC22v)
PIPL12v=ee$Labour[1:32]-mv12$eff*(ee$Labour[1:32]-IRPL12v) ##PIP or MB for input x in yr1 rel to F2
PIPE12v=ee$Energy[1:32]-mv12$eff*(ee$Energy[1:32]-IRPE12v)
PIPK12v=ee$Capital[1:32]-mv12$eff*(ee$Capital[1:32]-IRPK12v)
PIPG12v=ee$GDP[1:32]+mv12$eff*(IRPG12v-ee$GDP[1:32])#PIP or MB for output y in yr1 rel to F2
PIPC12v=ee$C02[1:32]-mv12$eff*(ee$C02[1:32]-IRPC12v)

PIPL21v=ee$Labour[33:64]-mv21$eff*(ee$Labour[33:64]-IRPL21v)#PIP or MB for input x in yr2 rel to F1
PIPE21v=ee$Energy[33:64]-mv21$eff*(ee$Energy[33:64]-IRPE21v)
PIPK21v=ee$Capital[33:64]-mv21$eff*(ee$Capital[33:64]-IRPK21v)
PIPG21v=ee$GDP[33:64]+mv21$eff*(IRPG21v-ee$GDP[33:64])#PIP or MB for output y in yr2 rel to F1
PIPC21v=ee$C02[33:64]-mv21$eff*(ee$C02[33:64]-IRPC21v)
round(data.frame(PIPL12v,PIPE12v,PIPK12v,PIPG12v,PIPC12v,PIPM12v,PIPL21v,PIPE21v,PIPK21v,PIPG21v,PIPC21v,PIPM21v),2)
```

#MEA CRS Efficiency scores#

EL11c=PIPL11c/ee$Labour[1:32] #level of input x eff = by how much x would have to be reduced for the unit to be x efficient

EE11c=PIPE11c/ee$Energy[1:32]

EK11c=PIPK11c/ee$Capital[1:32]

EG11c=ee$GDP[1:32]/PIPG11c #level of input y eff

EC11c=PIPC11c/ee$C02[1:32]

EL22c=PIPL22c/ee$Labour[33:64] #level of input x eff = by how much x would have to be reduced for the unit to be x efficient

EE22c=PIPE22c/ee$Energy[33:64]

EK22c=PIPK22c/ee$Capital[33:64]

EG22c=ee$GDP[33:64]/PIPG22c #level of input y eff

EC22c=PIPC22c/ee$C02[33:64]

EL12c=PIPL12c/ee$Labour[1:32] #level of input x eff = by how much x would have to be reduced for the unit to be x efficient

EE12c=PIPE12c/ee$Energy[1:32]

EK12c=PIPK12c/ee$Capital[1:32]

EG12c=ee$GDP[1:32]/PIPG12c #level of input y eff

EC12c=PIPC12c/ee$C02[1:32]

EL21c=PIPL21c/ee$Labour[32:64] #level of input x eff = by how much x would have to be reduced for the unit to be x efficient

EE21c=PIPE21c/ee$Energy[32:64]

EK21c=PIPK21c/ee$Capital[32:64]

EG21c=ee$GDP[33:64]/PIPG21c #level of input y eff

EC21c=PIPC21c/ee$C02[33:64]

#MEA VRS Efficiency scores#

EL11v=PIPL11v/ee$Labour[1:32] #level of input x eff = by how much x would have to be reduced for the unit to be x efficient

EE11v=PIPE11v/ee$Energy[1:32]

EK11v=PIPK11v/ee$Capital[1:32]

EG11v=ee$GDP[1:32]/PIPG11v #level of input y eff

EC11v=PIPC11v/ee$C02[1:32]

EL22v=PIPL22v/ee$Labour[32:64] #level of input x eff = by how much x would have to be reduced for the unit to be x efficient

EE22v=PIPE22v/ee$Energy[33:64]

EK22v=PIPK22v/ee$Capital[33:64]

EG22v=ee$GDP[33:64]/PIPG22v #level of input y eff

EC22v=PIPC22v/ee$C02[33:64]

EL12v=PIPL12v/ee$Labour[1:32] #level of input x eff = by how much x would have to be reduced for the unit to be x efficient

EE12v=PIPE12v/ee$Energy[1:32]

EK12v=PIPK12v/ee$Capital[1:32]

EG12v=ee$GDP[1:32]/PIPG12v #level of input y eff

EC12v=PIPC12v/ee$C02[1:32]

EL21v=PIPL21v/ee$Labour[33:64] #level of input x eff = by how much x would have to be reduced for the unit to be x efficient

EE21v=PIPE21v/ee$Energy[33:64]

EK21v=PIPK21v/ee$Capital[33:64]

EG21v=ee$GDP[33:64]/PIPG21v #level of input y eff

EC21v=PIPC21v/ee$C02[33:64]