RENEWABLE ENERGY VALUE CHAIN DYNAMICS AND PRODUCTIVE SECTOR GROWTH IN KENYA

BY

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SCHOOL OF BUSINESS AND ECONOMICS

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DECLARATION

I certify that the content of this thesis is entirely my personal work and to the best of my knowledge, it has not been submitted in any form to any other institution for academic purposes.

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DEDICATION

To my beloved parents, especially my dear father,

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ABSTRACT

Despite Kenya's substantial progress in renewable energy development, productive-sector growth remains constrained, raising concerns about whether the country's renewable energy transition is translating into improved performance across agriculture, manufacturing and services. Between 2015 and 2023, agriculture contributed about 20.9% and manufacturing about 8.3% of Kenya's GDP, while services accounted for 55%. As of 2023, Kenya had an installed capacity of about 2,453MW, with 80–90% from renewable sources. However, persistent load-shedding, low grid-penetration and capacity utilization below 30% have created a structural energy gap, with net imports accounting for 22.3% of total energy use. Existing studies treat renewable energy stages in isolation and largely ignore transmission–distribution losses, despite their importance in determining usable electricity, costs, reliability and sectoral outcomes. The purpose of this study was to investigate the influence of renewable energy value chain dynamics on growth in Kenya's productive sector. Specifically, this study has examined the effects of renewable energy value chain dynamics on the manufacturing, services and agriculture sectors in Kenya. This study is anchored in an augmented Cobb–Douglas framework derived from the Solow–Swan growth model and adopts a correlational design. Time series data from 1980 to 2024 were sourced from WDI and EIA and analyzed using ARDL-ECM frameworks. Findings show that renewable energy consumption and installation significantly influence manufacturing, with $\beta = 6.517$ ($p = 0.001$) and $\beta = 44.405$ ($p = 0.037$) three years earlier, supporting the energy-led growth and endogenous growth theories that link reliable energy access to productivity expansion. Generation exhibits mixed effects, with $\beta = 24.554$ ($p = 0.010$) two years earlier, reflecting value chain dynamics and structural inefficiencies in energy systems, while transmission-distribution losses reduce output with $\beta = -48.318$ ($p = 0.011$) four years earlier, underscoring infrastructure constraints and efficiency losses. Service performance is positively influenced by consumption, with $\beta = 60.264$ ($p = 0.000$), consistent with demand-led growth theory, while generation shows persistent negative effects, with $\beta = -236.864$ ($p = 0.009$) two years earlier, indicating supply unreliability and inefficiencies. Transmission-distribution losses exert marginal negative effects. Agriculture responds to installation with mixed effects, with $\beta = 261.390$ ($p = 0.003$) one year earlier, reflecting structural adjustment, while consumption supports performance with $\beta = 10.899$ ($p = 0.049$) one year earlier. Transmission-distribution losses show marginal positive effects. These findings imply that strengthening energy efficiency, reducing losses and aligning renewable energy deployment with sector-specific needs are critical for lowering costs, enhancing productivity and advancing climate-resilient growth in line with Africa's Agenda 2063.

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ACRONYMS AND ABBREVIATIONS

ADF	Augmented Dickey-Fuller
AfDB	African Development Bank
AIC	Akaike information criterion
ARDL	Auto-regressive distributed lag model
BKWH	Billion Kilowatt Hours
COP28	28th Conference of the Parties to the United Nations Framework Convention on Climate Change (UNFCCC).
DSGE	Dynamic Stochastic General Equilibrium
EIA	Energy Information Administration (United States)
EPRA	Energy and Petroleum Regulatory Authority
ECM	Error correction model
EU	European Union
FiT	Feed-in-tariff
GDP	Gross Domestic Product
GESIP	Green Economy Strategy and Implementation Plan
GMM	Generalized method of moments
ICT	Information and communications technology
IPPs	Independent power producers
IRENA	International Renewable Energy Agency
J-B	Jarque-Bera
KenGen	Kenya Electricity Generating Company
KETRACO	Kenya Electricity Transmission Company
KNBS	Kenya National Bureau of Statistics

KW	Kilowatts
KPLC	Kenya Power and Lighting Company
MW	Megawatt
OECD	Organization for Economic Co-operation and Development.
REREC	Rural Electrification and Renewable Energy Corporation
UNIDO	United Nations Industrial Development Organization
WDI	World Development Indicators
SDG	Sustainable Development Goal
UNDP	United Nations Development Programme
US	United States
USD	United States Dollar
VECM	Vector Error Correction Model
VIF	Variance Inflation Factor

OPERATIONAL DEFINITION OF TERMS

Agriculture value added	Agriculture, forestry and fishing corresponds to ISIC divisions 1-3 and includes forestry, hunting and fishing, as well as cultivation of crops and livestock production. Value added is the net output of a sector after adding up all outputs and subtracting intermediate inputs.
Green energy	Energy generated from sources that are renewable, environmentally friendly and low in greenhouse gas emissions.
Grid penetration rate	Describes how much of the installed capacity is converted into usable electricity and made available to the consumers.
Gross capital formation	The total value of investments in fixed assets, inventories and improvements to existing capital that increase an economy's productive capacity within a given period.
Labour	Human effort, both physical and intellectual, is employed in the production of goods and services within an economy.
Load-shedding	Refers to the art of reducing stress exerted on energy sources when the energy demand is greater than the primary supply.
Manufacturing value added	Manufacturing refers to industries belonging to ISIC divisions 15-37. Value added is the net output of a sector after adding up all outputs and subtracting intermediate inputs.
Power blackout	A power outage, loss or failure
Renewable Energy Consumption	Energy usage derived from natural resources, for instance, sunlight, wind, rain, geothermal and heat, which are renewable and do not suffer from the fear of depletion.

Renewable Energy Generation	Refers to the process of producing energy from renewable resources.
Productive sectors	Refers to the manufacturing, service and agriculture sectors.
Transmission-Distribution losses	Refers to the loss of electrical energy that occurs as electricity travels from power plants to end users.
Ramp-up rate	Describes the rate at which installed renewable capacity is brought online and exploited to meet demand.
Renewable energy	These are energy forms considered inexhaustible.
Renewable Energy Installation	Process pertaining to the setting up of infrastructure and facilities that generate energy from renewable resources. It is simply renewable energy investment expressed in megawatts. Renewable energy installation and renewable energy investment will be used interchangeably in this study.
Renewable Energy Production	Refers to producing energy using renewable sources like solar, hydro, geothermal, wind and biomass.
Renewable energy value chain dynamics	Activities revolving around installation, generation, consumption and net transmission-distribution losses of renewable energies.
Renewable Energy Transition	Shift from the adoption of non-renewable energy sources to stop climate change. In this study, this term specifically refers to the adoption of renewable energy installation, generation, consumption and losses to avert undesired climatic outcomes.
Services Value Added	Services correspond to ISIC divisions 50-99. They include value added in wholesale and retail trade (including hotels and restaurants), transport and government, financial, professional and personal services such as education, health care and real estate services.

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CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Performance of the productive sectors of the economy signifies efficiency and it therefore shows how effectively resources are exploited in the production processes. Globally, sectoral performance remains a critical indicator of overall economic health, improved living standards, facilitating income generation, employment creation and sustainable growth (Smith, 2020). In this study, productive sector consists of agriculture, manufacturing and service, with each of them contributing significantly to overall economic output. While manufacturing activities transform raw materials into finished goods, the service sector drives economic performance by providing essential services such as finance, transport, Information and Communication Technology (ICT), education and health; that enable production, raise productivity and create jobs and incomes across the economy. Agriculture supports the economy by ensuring the populations are supplied with adequate food, raw materials and employment opportunities for the rural folks. These three sectors contribute to a balanced economy by ensuring value addition, growth and sustainability for the ever-rising populations (World Bank, 2021).

Globally, the agricultural sector is essential in guaranteeing that there is adequate food for the populations and raw materials for the industries and also provides job opportunities in both developing and developed economies, besides contributing about 4.3% to the global GDP (Food and Agriculture Organization of the United Nations, 2020). According to the report, agricultural activities in the developed world are highly mechanized and technology-driven, significantly boosting their growth.

According to Clark (2025), the manufacturing sector is a key facilitator of modernization and global competitiveness and contributes about 26% of the worldwide GDP. Economies like China and South Korea have achieved rapid sectoral growth through industrialization, which relies heavily on reliable energy to run. The services sector has seen exponential growth globally, contributing over 66% of the global GDP, becoming a dominant contributor to GDP in many developed economies, mainly motivated by innovations in Information and Communication Technology(ICT), finance, as well as healthcare. Globally, energy serves a very critical role in driving the growth as well as development relating to the sectors of the economy; without sufficient energy, sectoral growth cannot reach the desired levels. Besides

energy constraints, the growth of these sectors is also impeded by political instability, climate change impacts and corruption-related activities (World Bank, 2021).

In Africa, sectoral performance remains largely constrained by structural challenges, with energy insufficiency among the most prevalent barriers. Agriculture accounts for approximately 60% of employment and about 23% of Africa's GDP. Yet, sectoral performance remains low due to limited access to mechanization systems, both of which are highly energy-dependent (FAO, 2020). The manufacturing sector, which is critical for Africa's transformation as per the African Union's Agenda 2063, has lagged on account of unreliable power supplies and the ever-rising costs of production, with high costs of power contributing immensely to these high costs (United Nations Industrial Development Organization, 2019). Energy constraints affect nearly 600 million people across the Saharan hinterlands of Africa, stifling manufacturing capacity and thereby reducing the competitiveness of African products in international trade. The services sector, which includes services from activities such as banking, tourism and telecommunications, has grown in recent years but remains vulnerable to energy disruptions, particularly in fast-growing ICT economies. Therefore, energy inadequacies and inefficiencies continue to impede Africa's ability to achieve its sectoral performance and development aspirations. (African Development Bank, 2016).

Regarding the East African Community, EAC (2021) reports that the manufacturing services and agriculture sectors contribute approximately 8-10%, 50-55% and 25-30% to the region's GDP, respectively. However, the EAC faces several challenges in enhancing the performance of these sectors. In agriculture, unreliable energy access impedes the adoption of modern irrigation infrastructure, leading to dwindling performance and post-harvest losses. The manufacturing sector suffers from high energy costs and frequent power outages, load shedding and blackouts, thus leading to frequent stoppages of the manufacturing and processing activities, hindering the much-desired 24-hour economies. Services in urban centers face similar challenges with inconsistent power supply negatively impacting telecommunications, financial services and digital performance. Energy challenges are particularly acute, as not more than half of the region's populace has power access and even where grid access exists, transmission losses and inefficiencies persist. This results in energy constraints, which impedes overall sectoral performance in the region (International Renewable Energy Agency, 2020).

In Kenya, sectoral performance faces similar energy-related problems despite their immense contribution to job creation, infrastructural development, enhanced innovation and entrepreneurship in Kenya. Agriculture, a sector that contributes 26.2% to the country's GDP and employs approximately 70% of the labour force, is impeded by insufficient energy for mechanization, irrigation and agro-processing (Kenya National Bureau of Statistics, 2024). Despite advances in renewable energies in Kenya, only a paltry 30% of its potential ends up being utilized and 22% of the aggregate energy generated is unaccounted for (Energy and Petroleum Regulatory Authority, 2022). Manufacturing, which contributes approximately 7.6% to GDP, is similarly impacted by high energy costs, persistent power outages and load-shedding, which drive up production costs and limit the competitiveness of Kenyan industries and their output (UNIDO, 2019). The services sector accounts for about 48-56% of GDP and is also greatly impeded by the energy disruptions that inhibit growth in ICT and finance, which are critical components of Kenya's digital economy. Despite their contribution to certain negative environmental externalities such as increased carbon emissions, air pollution and ecosystem degradation, as well as inequalities including uneven access to modern energy services between rural and urban areas and disparities in the distribution of economic benefits across regions and income groups, efforts should still be made to promote sectoral growth due to its innumerable positive impacts on the population, including employment creation, income generation and improved standards of living.

Addressing these energy-related problems is critical for Kenya's dream of achieving sectoral growth rates of about 8-10% annually and realizing the broader development objectives as set out in Vision 2030 and Agenda 2063 (African Union, 2015). Kenya's economic and sectoral performance has struggled to keep pace with the ever-increasing population in recent years. This is because while overall sectoral performance seems to be increasing at an arithmetic rate of 2-6% annually according to KNBS (2025) against the recommended 8-10%, the population is increasing exponentially, thereby raising sustainability issues. The country's population continues to grow at an annual rate of about 2.3%, while sectoral growth has been has failed to keep pace, driven by external factors such as global commodity prices, inflation, adverse political climates, exorbitant energy prices and fiscal constraints. Kenya's economy grew by 4.8% in 2022, representing a significant decrease from the robust 7.5% growth in 2021. However, the World Bank forecast that the country's economic and sectoral growth will grow by 5% in 2022-2025 and continue with modest increases in subsequent years. Although promising and impressive, these figures may still lag behind the needs of a rapidly

growing population, putting pressure on important parameters such as healthcare, education and employment opportunities. Addressing structural issues such as renewable energy installation, generation, consumption and transmission-distribution losses in manufacturing, services and agriculture and improving investment in green technologies may help bridge this gap. All these sectoral growth mechanisms are heavily energy-reliant (World Bank, 2023). Therefore, without significant improvements in energy access and efficiency, Kenya risks stagnating in its pursuit for sustainable sectoral performance.

The significance of energy in spurring any country's economic development and industrialization can never be overstated. Energy is a fundamental pillar of economic activities in economies (Singh *et al.*, 2019). However, overreliance on non-renewable energy sources poses risks due to their finite nature and negative environmental externalities. Therefore, there is a shift towards green energy globally, which is considered sustainable and environmentally friendly (Vera & Langlois, 2007). Environmental friendliness and sustainability are, therefore, the key attributes of renewable energy sources. Renewable energy's sustainability attribute is owed to the fact that there is always no fear of depletion, hence being referred to as energy for the future. It is a form of energy capable of supplying current and future populations' energy requirements without fear of depletion (Guliyev & Tatoglu, 2023). Therefore, renewable energy exploitation should be encouraged as it gives impetus to the process of industrialization and accelerates economic and sectoral activity without adversely impacting the environment. This desire for environmental sustainability is also one of the key 28th Conference of the Parties to the United Nations Framework Convention on Climate Change (COP28) outcomes that advocated for enhanced emission reduction targets, fossil-fuel phase-out and adoption of nature-based solutions. It's for this reason that the COP28 convention advocated for investment in renewable energies, tripling the renewable energy capacity by 2030 by doubling the renewable energy grid and storage capacities. Environmental sustainability, through the adoption of green energy solutions, is also the key focus area of the COP29, with a key focus on increasing renewable energy capacity, climate finance for renewables as well as the adaptation of the Climate Reparations Fund.

From a global perspective, highly industrialized economies heavily rely on renewable energies to guarantee a sustainable energy supply, making them important ingredients of economic development (Singh *et al*., 2019). Furthermore, renewable energy is affordable, cost-effective and has positive environmental effects such as lower carbon emissions and its role in decarbonization. Besides job creation, investments in renewable energy development help rural

enterprises become self-sufficient in energy (Bekun *et al*., 2019). Due to its affordability and accessibility to even the households and settlements that are located far away from the national grid, the underserved fragments within the population, with other energy forms, would still prefer to have renewable energies in addition to the different forms.

From an African perspective, the African Union's Agenda 2063 provides a strategic framework that ensures inclusive and sustainable development. One of its key goals emphasizes environmentally sustainable and climate-resilient economies, prioritizing healthy consumption and production trends, including embracing green energy alternatives. Therefore, it is crucial to invest in interventions that not only advocate for the general economic health of the African communities but also emphasize the long-run sustainability of both the energy consumption behavioural patterns and ensure environmental sustainability. Africa's energy situation is characterized by significant challenges and opportunities, with about half of the African population lacking access to reliable electricity, a phenomenon more prevalent in rural areas. Despite the massive renewable energy capacities, a significant portion of African countries utilize fossil-based energy sources like biomass. This yields both environmental and energy insufficiency concerns. However, there are concerted measures aimed at more investments in renewables to expand the grid and off-grid solutions. That way, the continent is poised to make significant strides toward an energy-sustainable future that is also environmentally conscious (Mandelli *et al.*, 2014).

In Kenya, the overreliance on depletable energy supplies in Kenya threatens future energy demands and economic progress. Investments in renewable energy and value-adding manufacturing productive activities are necessary for achieving the industrialization and economic growth aspirations of any economy (Xu *et al*., 2019). This is because manufacturing adds value to locally produced goods so that they fetch competitive prices in the global market compared to dealing in fresh and unprocessed produce. Since manufacturing uses a significant amount of energy, growing its share of GDP can promote sectoral and overall economic growth (Obange *et al.*, 2013). According to Palmer (2012), poverty alleviation, unemployment reduction and general quality of life enhancement depend on the performance of the economic sectors. Implementing policies targeted at boosting aggregate demand through industrialization and value addition is necessary to accomplish this. However, attempts at modernization and economic performance may be inhibited by a lack of adequate and sustainable energies.

Energy plays a central role in achieving the majority of Kenya's SDGs, both directly and indirectly. It underpins SDG 7 by promoting cost-effective and eco-friendly energy solutions, contributes to SDG 1 through poverty alleviation and supports SDG 2 by enhancing agricultural productivity to reduce hunger. Energy also facilitates SDG 3 on quality education, SDG 5 on gender equality by reducing the time girls and women spend collecting firewood and water, SDG 8 by fostering dignified work and overall prosperity and SDG 9 through the development of industry, innovation and infrastructure. Furthermore, it enables SDG 11 on sustainable cities and communities via robust transport systems, SDG 12 through conscious resource utilization, SDG 13 on environmental and climate response, SDG 15 by protecting terrestrial and marine biodiversity through responsible energy practices and SDG 17 by fostering partnerships to achieve global energy objectives (UN, 2015). The availability of sufficient and reliable energy is therefore critical for the attainment of these goals.

Furthermore, energy will play an integral part in actualizing the bottom-up economic transformation agenda adopted by the Kenyan government in 2022. The bottom-up economic transformation agenda, as fronted by the Kenyan government, seeks to address the needs of disadvantaged populations by empowering them directly by fostering sustainable and inclusive economic growth (Cassina & Gachara,2023). This proposition, though not strictly advanced by a single economic theory or school of economic thought, draws from several theories and traditions that champion inclusivity, grassroots development and the need to empower the economically disadvantaged sections of the population. These alleviation mechanisms such as the deliberate advancements in agriculture, education and training, healthcare, ICT, water and sanitation need huge amounts of sustainable energy to actualize. This proposition heavily borrows ideas from development economists such as Amartya Sen and Joseph Stiglitz. Although their implementation and success remain debatable, energy was to be a key pillar in the attainment of the botched Big 4 Agenda aspirations of affordable housing, universal healthcare, manufacturing and economic transformation. Therefore, energy is at the center of any country's economic, social and political transformation.

Therefore, energy plays a key role in Kenya's development agenda by acting as a catalyst for socioeconomic advancement. It is one of the essential pillars supporting the three key objectives of Vision 2030: economic growth, social development and political governance. To achieve Vision 2030 endeavors and overall socioeconomic development, Kenya must enhance energy installations and generation and improve efficiency in energy consumption. The country is also faced with the menace of energy losses, but it is well-endowed with green

energy reserves like hydroelectric power, geothermal, wind, solar and biomass. However, only a small proportion of these resources have been optimally exploited. If properly harnessed, these resources can significantly contribute to Kenya's energy supply mix. Although Kenya has made notable progress in assessing the potential of the various renewable energies, a comprehensive evaluation, mapping and appraisal of all renewable energy resources should be undertaken in a bid to assess their full potential (Oludhe,2013). This is why this study seeks to investigate the influence of renewable energy installation, generation, consumption and transmission-distribution losses so to offer a disaggregated and policy-oriented approach in harnessing the potential.

1.1.1 Sectoral Performance Patterns in Kenya: Trends, Challenges and Global Context

The Kenyan economy is driven by the performance of its manufacturing, agricultural and service sectors. Understanding the trends, contributions and constraints of these sectors is critical for analyzing national economic performance. Manufacturing involves transforming raw materials into usable products and is a key contributor to national output and employment creation (Groover, 2016), thus highlighting the sector's importance in accelerating economic development. Any reduction in manufacturing activity significantly affects the economy, as manufacturing and industrial activities are central to poverty alleviation, bridging income disparities and reducing unemployment (Adekoya *et al.,* 2021). The sector comprises subsectors such as textiles, apparel, farm product transformation, building materials, leather products, fish handling, industrial plants, healthcare equipment, automobile, ferrous metals, digital technology, wood products, oil, mining and gas (Okeyo, 2022; Adekoya *et al.,* 2021).

Processed goods also command higher prices in global markets than unprocessed goods, thereby improving Kenya’s balance of payments. Manufacturing activities create jobs, reduce poverty, foster industrial development and connect with other economic sectors (Okeyo, 2022; Adekoya *et al.,* 2021). They also boost employment in transport, logistics, financial services, ICT, housing, healthcare and agriculture (Okeyo, 2022). However, high energy costs and dilapidated infrastructure challenge manufacturing performance, causing frequent power outages, load-shedding and low investor confidence. Energy availability is critical, as manufacturing is energy-intensive; any policy that fails to ensure sufficient energy limits industrial performance (Walther & Weigold, 2021). Manufacturing adds value to agricultural products such as tea, opens new industrial markets and strengthens exports (Zheng *et al*., 2021; Lv *et al*., 2020). Sarkodie and Adom (2018) emphasize that a reliable energy supply is a prerequisite for sustaining manufacturing activities and overall economic development,

aligning with Raza *et al.* (2016). Historically, Kenya has struggled with energy supply to spur industrial activities, with high costs and outdated infrastructure causing blackouts and suppressed growth (IRENA, 2018). In 2023, Kenya's manufacturing sector grew by approximately 2.0 %, remaining well below the country's industrial growth aspirations for long-term economic transformation (KNBS, 2025). Addressing energy constraints is therefore crucial to achieving manufacturing growth and meeting the aspirations of Vision 2030.

Agriculture, encompassing crop cultivation and livestock rearing, is the backbone of Kenya's economy (FAO, 2018). It provides employment, ensures food security, contributes to global trade and strengthens currency against trading partners (Bathaei & Streimikiene, 2023). Agricultural activities require energy for weed and pest control, harrowing, furrowing, harvesting, drying, transportation and distribution. Access to sustainable and efficient energy improves productivity and minimizes losses. Agricultural output also promotes social equity, community engagement, climate adaptation and economic resilience. Agriculture contributes 15% of Africa's GDP. Inefficiencies in energy use highlight the need for energy-efficient machinery to optimize production and growth. In 2023, Kenya's agricultural sector grew at 3.0%, with a target of 8-10% by 2030 (KNBS, 2023). Energy limitations, climate change, political instability, corruption, limited finances and outdated technologies suppress growth (IEA, 2023; World Bank, 2023; United Nations Development Programme, 2023). Mitigating these factors is crucial for sustainable agricultural development, in Kenya and beyond.

Kenya's service sector encompasses all activities providing services rather than tangible goods, including transport, ICT, finance, education, healthcare and professional services (Kotler & Keller, 2016; Mwarange, 2022). In developed economies, services dominate GDP with 61-70%, while in developing nations, they contribute 42-55% (Mashayekhi, 2020; Mwarange, 2022). Kenya's services enhance economic growth by providing critical inputs to agriculture and manufacturing. The sector is energy-intensive and green energy solutions, such as electric vehicles, are gaining traction globally, supporting sustainable service delivery (IEA EV Outlook, 2024). Historical contributions of service subsectors show variability: retail and wholesale, 7.9-8.3%, logistics, 10.2-11.7%, hospitality, 0.7-1.2%, ICT, 2.4-2.7%, finance and insurance, 6.5-7.8%, property, 8.9-9.4%, professional services, 2.3-2.9%, public administration, 5.2-5.5%, education, 3.9-4.5% and health, 1.9-2.1% (KNBS, 2021). In 2023, the service sector grew at 4.5% with a Vision 2030 target of 8-10% (KNBS, 2023). Energy insufficiency, high operational costs, limited financing, administrative hurdles and workforce skill gaps constrain growth (IEA, 2023; World Bank, 2023; UNDP, 2023).

Globally, as of 2022, services, manufacturing and agriculture contributed 65%, 28% and 7% to GDP, respectively. In Africa, services contribute approximately 53%, manufacturing contributes about 25% and agriculture contributes about 15-22% (World Bank, 2023). Global challenges, including COVID-19, geopolitical tensions and monetary tightening, have reduced global productivity from 3.1% in 2022 to 2.1% in 2023, with marginal recovery expected beyond 2024 (World Bank, 2023). African sectoral performance is constrained by inflation, political instability, energy deficits and climate impacts, threatening food security and economic stability.

Kenya's sectoral contributions for the period 1980-2022 show that agriculture declined from 28.02% to 19.41%, manufacturing remained at about 10% and services rose from 48.17% to 56.12% (KNBS, 2021). Recent trends show services driving GDP, agriculture maintaining critical importance and manufacturing striving to improve despite energy and infrastructural challenges (Statista, 2024).

The sectoral analysis highlights that energy availability and efficiency are critical bottlenecks affecting performance across manufacturing, agriculture and services. High energy costs, unreliable supply and outdated infrastructure suppress sectoral output and deter investments. Practically, this emphasizes the need for energy-focused interventions to enhance productivity. From a research perspective, there is limited empirical evidence in Kenya quantifying the impact of the renewable energy value chain dynamics on sectoral performance. This gap motivated this study, which sought to examine the influence of renewable energy value chain dynamics on the performance of the manufacturing, agriculture and service sectors in Kenya.

1.1.2 Global Renewable Energy Situation

Global electricity demand has continued to rise over time, reaching more than 30,000 terawatt-hours in 2023 (IEA, 2024). Despite growth in generation, significant inefficiencies remain in the energy value chain. According to World Bank (2025), nearly two-thirds of the world's primary energy is lost through conversion, transmission-distribution inefficiencies, raising serious concerns about sustainability and efficiency. In Africa, electricity generation remains substantially below demand, contributing to widespread supply deficits and energy insecurity (IEA, 2024). Regarding the global energy mix, fossil fuels still dominate, with oil, natural gas and coal together accounting for more than 75% of primary energy use worldwide**,** while Africa's energy mix is even more heavily reliant on oil and gas (Our World in Data, 2024). Although there is a global shift toward renewable energy, many regions remain dependent on

traditional non-renewable sources to sustain production activities. Enhance the global framework.

In Africa, electricity generation continues to lag significantly behind demand, reinforcing persistent energy deficits and limiting productive capacity across economies. According to the International Energy Agency (2024), a large proportion of the continent's population still lacks reliable access to electricity, while existing systems are characterized by low generation capacity and weak transmission infrastructure. Although the region possesses abundant renewable energy potential, particularly in solar, hydro and geothermal resources, its energy mix remains heavily dependent on fossil fuels, especially oil and natural gas, as reported by Our World in Data (2024). Furthermore, inefficiencies in energy conversion, transmission-distribution, highlighted by the World Bank (2025), continue to constrain the effective utilization of generated power. As a result, Africa faces a structural imbalance between energy supply and demand that undermines industrialization, agricultural productivity and service-sector expansion, despite ongoing efforts to scale up renewable energy investments.

Within East Africa, the energy challenge is similarly pronounced, although the region has made notable progress in expanding renewable energy capacity. Countries such as Kenya, Ethiopia and Tanzania have increasingly invested in hydropower, geothermal and wind energy, positioning the region as a leader in renewable energy adoption on the continent. However, according to the International Energy Agency (2024), electricity access and reliability remain uneven, particularly in rural and peri-urban areas, where grid penetration is still limited. In addition, reports from the World Bank (2025) indicate that transmission-distribution losses remain substantial, reducing the amount of usable electricity available for productive activities. Despite the growing share of renewables in the energy mix, dependence on supplementary non-renewable sources persists to stabilize supply and meet rising demand. Therefore, the region continues to experience energy supply inconsistencies that constrain sectoral growth, highlighting the need for more efficient integration of renewable energy into the broader economic system.

1.1.3 Kenya's Renewable Energy Situation

According to KNBS (2023), approximately 80-90% of Kenya's energy portfolio comprises renewable sources, with the remaining 10% coming from nonrenewable energy forms. Renewable energy comes from sources, for instance, solar, geothermal, wind and hydroelectric power play a pivotal role in Kenya's energy landscape, particularly in production processes

across various sectors. Kenya leads Africa in renewable energy installed capacity with a capacity of approximately 2,453 Megawatts (MW), projected to rise to 5,000 MW by 2030. This capacity is underpinned by key installations, including the Lake Turkana Wind Power Project, a significant Ksh 70 billion investment and the largest private energy investment in the country. These figures highlight Kenya's strong progress and leadership in renewable energy development within the region. However, they do not reveal whether this expanding capacity is effectively translating into growth across the manufacturing, services and agriculture sectors, thereby necessitating further empirical investigation.

The nation's hydropower resources are installed at the Seven Forks Dams along the Tana River, including Masinga, with a capacity of 40 MW, Kamburu, with a capacity of producing 94.2 MW, Gitaru, with a capacity of 225 MW, Kindaruma with a capacity of producing 72 MW and Kiambere, with a capacity of 168 MW, the Turkwel Gorge Dam, with a capacity of 106 MW as well as the Sondu Miriu Hydroelectric Power Station with a capacity of 60 MW (KPLC, 2023). Demand for hydropower is specifically abnormal because, as Lee *et al*. (2016) opines, about 90% of the populace who have access to other forms of off-grid electricity in Kenya still prefer to be hooked to the national grid. These figures highlight the substantial hydropower capacity supporting Kenya's national grid and its central role in energy supply. However, despite this strong reliance and preference for grid-based electricity, it remains unclear whether hydropower availability is consistently supporting productivity and growth across the key economic sectors, thereby warranting further empirical analysis.

The Olkaria complex is the primary source of Kenya's geothermal energy. The complex encompasses Olkaria I with a capacity of producing 185 MW, Olkaria II with a capacity of producing 105 MW, Olkaria III, with a capacity of producing 139 MW, Olkaria IV, with a capacity of producing 150 MW and Olkaria V, with a capacity of producing 158 MW, along with the Menengai Geothermal Project, with a capacity of producing 105 MW and the Eburru Geothermal Power Plant, with a capacity of producing 2.5 MW (KenGen, 2022). These figures demonstrate the significant expansion of geothermal energy capacity and its growing contribution to Kenya's energy mix. However, the extent to which this sustained increase in geothermal production translates into enhanced performance across key economic sectors remains uncertain, thus necessitating further empirical investigation.

Wind power exploitations are undertaken at the Lake Turkana Wind Power Project, an establishment in the Northern part of Kenya with a capacity of producing 310 MW. They are

complemented by the Ngong Hills Wind Power Station, located in Ngong, with a capacity of producing 25.5 MW and the Kipeto Wind Farm, with a capacity of producing 100 MW (KPLC, 2023). Several small wind power stations contribute to the wind power mix; the Kakamega wind farm in western Kenya, with a proposed capacity of 10MW, the Nyandarua wind power project in Nyandarua, with a capacity of producing 50MW when complete and the Meru Wind Power Station, with a capacity of producing 20 MW when complete (IRENA,2023). These figures reflect installed capacities and commonly reported generation estimates, though actual output may vary depending on climatic conditions, grid stability and transmission efficiency. These figures illustrate Kenya's growing diversification of wind energy infrastructure, anchored by large-scale and emerging projects across different regions of the country. However, despite the expanding installed capacity, the actual contribution of wind power to sustained economic performance across key productive sectors remains uncertain, necessitating further empirical investigation.

Solar energy is harnessed at the Garissa Solar Power Station, with a capacity of 55 MW, the Malindi Solar Power Station with a capacity of 40 MW and other smaller projects, contributing significantly to Kenya's energy mix (KPLC, 2023). The uptake of solar energies in Kenya has been boosted by the existing solar energy financing interventions, such as M-Kopa and Sunking solutions. However, this initiative has not translated to the desired solar energy uptake since Kenyans are generally risk-averse and cautious, hence they do not easily take up the loaned products due to fear of possible auctioning as a result of loan defaulting. Kenya receives an average of 6.5 sunshine hours daily, but the uptake of solar energy in Kenya is being inhibited by insufficient data regarding spatial variations of solar power capacity (Oloo *et al.,* 2015). However, the real-time quantities of renewable energies produced and consumed fall short of installed capacities due to inefficiencies such as frequent power blackouts and high energy costs (Shah, 2019). This study therefore aims to provide a detailed sectoral analysis of actual solar energy production and consumption to identify inefficiencies and inform strategies for maximizing the contribution of solar energy to Kenya's energy mix.

Kenya also has massive potential for biomass energy that is derived from agricultural residues, wood and animal wastes. Biomass constitutes about 70-80% of the overall energy portfolio at the household level and is exploited primarily in cooking and heating. However, this important sector faces challenges such as unsustainable harvesting, inefficient technologies, environmental degradation, limited investment in modern biomass systems and inadequate policy support (Namaswa *et al.,* 2022). This study, therefore, seeks to examine the production,

consumption and losses in the renewables energy sector to identify inefficiencies and opportunities for sustainable and more efficient utilization in Kenya.

In terms of renewable energy generation as of 2023, EPRA (2023) reports that Kenya's renewable energy sector plays a critical role in meeting its electricity demand, with hydropower generating about 826 MW, which is about 30-40% of the total generation. Geothermal power, Kenya's most stable renewable energy source, generates just over 950 MW, meeting approximately 40% of the grid electricity and positioning Kenya as Africa's champion in geothermal power-generating ability. Solar energy generates around 50 MW, mainly through distributed off-grid systems in rural areas, as grid-integrated solar remains limited. Wind power, mainly generated from the Lake Turkana Wind Power Station, an establishment in Athwana, with a generating capacity of just about 310 MW, helps address peak demand. Together, these renewable energy sources contribute about 2,261 MW. Cumulatively, Kenya produced approximately 12 terawatt-hours of electricity but faced a demand of 14 terawatt-hours over the same period. The primary reasons for these energy gaps are inefficiencies in the renewable energy value chain as well as a continuous increase in electricity demand that surpasses the generation capacities. The low ramp-up and grid penetration rates also account for these energy shortfalls. These shortfalls lead to persistent power blackouts and load-shedding in the energy value chain. (Our World in Data, 2024). These figures indicate that although Kenya's renewable energy mix makes a substantial contribution to national electricity generation, supply still falls short of rising demand due to persistent system inefficiencies and infrastructure constraints. Thus, frequent energy shortfalls and instability in supply raise critical concerns about whether the existing renewable energy capacity is sufficient to sustainably support productive sector growth.

With regard to renewable energy consumption, Kenya's electricity demand has steadily increased from 1.662 BKWH in 1980 to 10.002 BKWH in 2023, while domestic production has grown alongside demand. Electricity imports have fluctuated over time. In 2023, they accounted for 22.3% of total energy use, highlighting a persistent reliance on external sources. This figure, based on data from the EIA, highlights a structural energy gap between domestic supply and demand. Addressing this gap is critical for supporting continuous economic activity and enhancing sectoral growth. (EIA, 2023). These figures reveal a sustained increase in electricity demand alongside rising domestic production, yet a persistent structural gap remains as reflected in continued reliance on imports. However, this imbalance raises important

concerns about the adequacy and reliability of energy supply in fully supporting consistent economic activity and sectoral growth in Kenya.

It is therefore apparent that Kenya has made great strides as far as renewable energy exploitation is concerned. However, this energy sector faces challenges such as the variability of renewable sources and inadequate grid infrastructure, leading to issues like low ramp-up rates and limited grid penetration rates. These problems contribute to frequent load-shedding and blackouts, making it difficult to ensure a reliable energy supply. Lee (2022) and Ambani (2024) assert that these blackouts and persistent cases of load-shedding are an economic menace to Kenya's prosperity. Additionally, the financial burden of renewable energy technologies and gaps in regulatory enforcement further inhibit the sector's performance.

Regarding the uptake of green energies, the adoption of this sustainable energy form has exhibited increasing trends, with about 90% of Kenya's complete energy portfolio coming from renewables (KNBS, 2022). As of 2021, renewable energy consumption accounted for approximately 1,080 million kilowatt-hours, coming from hydroelectric power, which comprised about 45% of the total renewable consumption, followed by geothermal energy at approximately 42% and wind energy at about 13% (EPRA, 2022). These trends demonstrate Kenya's resolve to lessen its dependency on nonrenewable energy solutions. Still on consumption, Kiplagat *et al.* (2011) asserts that renewables constitute just over 80% of the total energy consumed in Kenya and suggests that efforts must be made to increase its uptake as it is sustainable given its replenishment ability. The study, however, notes that a limited percentage of Renewable energy options in Kenya are exploited; with only 30% exploitations in hydropower,4% in geothermal power and much lower percentages attached to wind and solar energies. This adds to the evidence of the problem of low ramp-up and grid penetration ratios. This is evidence of the insufficient utilization of Kenya's clean green energy endowment.

Kenya's service, agricultural and manufacturing sectors increasingly rely heavily on renewable energy, yet a significant demand and supply gap persists. The combined energy demand for these sectors exceeded 4,500 MW in the year 2023, with supply from renewable energy forms falling short by approximately 1,200 MW, leading to reliance on non-renewable sources to bridge this gap (Ministry of Energy, 2023). These figures indicate a clear structural imbalance between energy demand and renewable energy supply across Kenya's key productive sectors. However, this persistent shortfall raises critical questions about whether renewable energy

expansion is sufficiently aligned with the energy requirements needed to sustain performance in the manufacturing, service and agriculture sectors.

In its evaluation of the renewable energy situation and potential in Kenya, Kiplagat *et al.* (2011) opines that a paltry 18% of the dwellings were connected to the national grid. This accessibility to the national grid was found to be much lower in the rural setups, where only a meager 4% were connected as of 2011. Owing to the opening up and the adoption of interventions that increase the utilization of renewables, more people are now able to access electricity, whether for their homes or businesses, improving their daily lives and opportunities. Over 35% of Kenyans have since been connected to the national grid (Muthamia,2016).

The manufacturing sector, which is heavily reliant on a stable power supply, particularly benefits from geothermal energy, while the agricultural sector, including irrigation and agro-processing, increasingly utilizes solar and small hydropower plants. The service sector, which encompasses tourism, banking and education, also depends on a consistent power supply from renewable sources. Nevertheless, the shortfall highlights the need for expanded renewable energy installations and efficient transmission networks to meet growing demands. Additionally, the Ministry of Energy Kenya (2020) highlights improving energy efficiency to minimize wastage and increase availability, a key factor in Kenya's goal of becoming a middle-income economy by 2030. The intervention might be key in curbing the persistent power outages and load-shedding that greatly impedes sectoral performance.

The emergence of independent power producers (IPPs) since 1997 has partially addressed the energy gap between supply and demand for energy. The IPPs supplied approximately 25% of the power purchased by the KPLC as of 2020. However, despite attempts to bridge the energy gap, there is still a shortage in supply, which leads to higher energy costs and prices. The high energy prices are a disincentive to economic production and therefore serve to suppress economic growth in the economy (Ministry of Energy, 2023).

According to Maleka (2024) and Mabuza and Maphosa (2023), persistent power blackouts and load-shedding resulted in increased crime rates and less secure environments that were a disincentive to South Africa's economic advancement. The study established that persistent load-shedding and power blackouts in South Africa, which stemmed primarily from grid failure, disrupted people's daily lives and negatively impacted productivity in the South African nation. it concluded, therefore, that load-shedding has economic, social, educational, psychological and infrastructural impacts which affect the well-being of a population.

Therefore, suppressed grid penetration and spiraling ramp-up rates, which eventually lead to persistent power blackouts and load-shedding should be addressed if meaningful and sustainable development is to be achieved.

This study, therefore, focuses on renewable energy because it can't be depleted and have massive potential in securing energy for both the existing and future requirements. The ever-increasing power demands from agriculture, services and industry have sent energy economists back to the drawing board so as to determine how these demands can be met, considering the rapid depletion of non-renewable resources (Munene *et al*., 2019). Emphasizing the funding as well as the uptake of green energies in Kenya is essential, as it is sustainable, environmentally friendly, reliable and inexhaustible, ensuring the ability to meet future energy needs without compromising future energy demands. This study, therefore, aimed at examining the associations existing between the green energy constructs and sectoral performance in Kenya.

Kenyan sustainable energy policy interventions have been essential in shaping the scaling up of green energy from renewable sources. The Energy Act (2019) have played a critical role in promoting investment, regulating the sector and creating a conducive environment for renewable energy development, leading to notable increases in wind, solar, geothermal and small hydropower capacities. For instance, the Feed-in Tariffs (FiTs) under the National Energy Policy guarantee fixed prices for electricity generated from renewable sources, thereby attracting private sector investments. Similarly, provisions for net metering allow households and businesses to sell excess electricity back to the grid, encouraging small-scale adoption of renewable energy systems; this intervention was first introduced in 2010 and revised in 2012 and 2018.

Other interventions aimed at promoting renewable energy uptake include the Kenya National Electrification Strategy (2018), which seeks to expand access to electricity across rural and urban areas; the Ministry of Environment and Forestry initiatives (2017), which focus on sustainable energy and environmental conservation; Vision 2030, which integrates renewable energy as a driver of economic performance; the carbon tax policy (Republic of Kenya, National Treasury and Economic Planning, Draft 2023), designed to incentivize low-carbon energy solutions; the Climate Change Act (2016), which provides a legal framework for climate-resilient energy systems; Power Purchase Agreements, which ensure long-term contracts for renewable energy producers; the Geothermal Resources Act (1982, revised 2019), which facilitates exploration and development of geothermal energy; Energy Net-Metering

Regulations (2024), which encourage distributed renewable energy generation; the Green Economy Strategy and Implementation Plan (GESIP, 2016), which promotes environmentally sustainable growth; the Least Cost Power Development Plan (2021), which prioritizes cost-effective renewable energy investments; private sector investments and green financing schemes, which provide financial support for renewable projects and promotes clean energy access (Wanyonyi, 2020; Ministry of Energy, 2018; Wanjiku, 2022; Energy Act, 2019; Muhoro & Gitonga Associates, 2024; FAO, 2016; Onsongo et al., 2024; Mulandi & Mwania, 2022; Odulaja et al., 2023). Each of these interventions has a clear objective of either increasing investment, improving access or incentivizing sustainable practices, thereby collectively encouraging greater uptake of renewable energy in Kenya. This study, therefore, seeks to evaluate the effectiveness of these renewable energy policy interventions in driving actual sectoral adoption, production and consumption, highlighting areas where uptake remains suboptimal and identifying opportunities for improvement.

Despite these green policy interventions, from both continental and local perspectives, Ockwell (2016) opines that two-thirds of the population in Sub-Saharan Africa is not connected to power, a key component in poverty alleviation. It suggests the need for a sustainable energy policy to bridge this gap. It suggests that policy needs to meet the billions spent on energy halfway if meaningful bridging of the gap is to be achieved.

According to Shogren and Taylor (2008) and Allcott and Greenstone (2012), the evolution of eco-friendly energy forms in Kenya is guided by economic, technical, policy and behavioural components that affect installation, generation, consumption and energy losses. High upfront costs and limited access to financing remain significant barriers to adoption, as many investors and businesses hesitate to commit to long-term energy solutions due to loss aversion, a tendency to focus on immediate costs rather than future savings. Grid integration challenges, including outdated infrastructure and the intermittent nature of renewable sources, further contribute to inefficiencies and losses. Policy and regulatory uncertainties also play a role, as inconsistent incentives and slow bureaucratic processes discourage large-scale investments. Additionally, technological constraints, such as inadequate energy storage and high maintenance costs, hinder optimal generation and utilization. On the consumption side, behavioural factors like habit, resistance to change and present bias, where consumers prioritize short-term convenience over long-term cost savings, affect energy efficiency. Social norms and peer influence also shape decision-making, with businesses and households more likely to

adopt renewable energy when they see others doing the same. Institutional inefficiencies, including delays in policy implementation and a lack of coordination, further exacerbate energy losses. Addressing these economic and behavioural barriers through well-designed policies, targeted incentives and awareness programs can enhance renewable energy adoption, reduce losses and improve overall sectoral performance in Kenya.

With regard to transmission-distribution losses, Kenya experiences significant transmission-distribution losses within its renewable energy value chain, which poses a challenge to its economy. Transmission-distribution losses in Kenya range between 20-22% (KNBS, 2023), thereby reducing the energy available for economic consumption in the productive sectors. To address these issues, Kenya has been upgrading grid infrastructure, implementing advanced metering systems, expanding the capacity of renewables and adopting green energy technologies and infrastructure geared towards enhancing efficiency and reliability and also helping in attaining market, operational and economic efficiency (IEA, 2023).

As outlined in the (Ministry of Energy Kenya **(**2020), power is pivotal not only in the manufacturing sector but also in elevating Kenya to a middle-income economy by the year 2030. Therefore, minimizing unnecessary wastages in the energy value chain is essential in ensuring adequate energy availability for consumption. Energy inefficiency can be operational, economic or market-based. The primary objective of optimized energy utilization is to encourage leveraging of smaller amounts of energy without compromising output quality or quantity, which requires deploying infrastructure and technology that consumes less energy for the same tasks.

1.1.4 Linking Renewable Energy Value Chain Dynamics to Sectoral Performance

A clear understanding of how renewable energy installation, generation, consumption and transmission-distribution losses interact with manufacturing, services and agricultural production is essential for explaining Kenya's sectoral growth patterns. Increases in renewable energy installation expand the country's clean energy infrastructure and create the foundation upon which actual renewable generation can rise, thus directly influencing the amount of affordable and reliable electricity available to productive sectors. When renewable energy generation improves, manufacturing firms benefit through reduced input costs and fewer power disruptions, the services sector gains from enhanced digital efficiency and continuous operations, while agriculture experiences more stable access to energy for irrigation, mechanization and value addition activities. Renewable energy consumption then reflects the

extent to which households and firms effectively utilize this generated power, thereby translating energy availability into real economic activity across the three sectors. However, renewable energy transmission-distribution losses, stemming from transmission inefficiencies, ageing grid systems and technical challenges, serve to limit the volume of energy that reaches end users, thus weakening the positive effects of installation, generation and consumption on sectoral output. Hence, these four renewable energy value chain dynamics form the core explanatory variables that shape the performance of manufacturing, services and agriculture, thereby justifying their inclusion as key determinants of Kenya's sectoral performance in this study.

This study is motivated by the critical need to understand how energy constraints impede Kenya's ability to achieve its sectoral performance targets as outlined in global, regional and national development frameworks. The SDGs by the UN assert that developing economies must accelerate sectoral growth to match rapidly expanding populations, thereby fostering innovation, technological advancement and overall economic development (United Nations, 2015). Similarly, the East African Community Vision 2050 emphasizes 10–12% annual sectoral growth to meet the region's demographic pressures (East African Community, 2016), while the African Development Bank's High 5 Agenda calls for substantial improvements in sectoral performance to attain sustainable development (AfDB, 2016).

At the national level, Kenya's National Industrialization Policy Framework (2013–2030) and the World Bank's Country Partnership Framework set ambitious sectoral growth targets of 8–10% to realize Vision 2030 and meet the country's demographic and economic ambitions (Government of Kenya, 2013; World Bank, 2020), a position also emphasized by the IMF (IMF, 2023). However, reports by KIPPRA (2022), AfDB (2022), EPRA (2023) and KNBS (2023) indicate that the attainment of these targets is significantly constrained by persistent energy insufficiency, high costs and systemic inefficiencies throughout the renewable energy ecosystem. In agriculture, inadequate energy access limits mechanization and cold storage, resulting in post-harvest losses and reduced productivity (FAO, 2020); in manufacturing, unreliable power supply diminishes competitiveness and industrial output (EPRA, 2022); and in the services sector, frequent power interruptions undermine investor confidence. Hence, despite marginal sectoral growth, 33% of the population remains below the poverty line and youth unemployment is approximately 18% (KNBS, 2023), highlighting the critical link between energy availability and the successful realization of these development goals.

Addressing energy-related barriers is therefore essential to support sustainable sectoral growth, fulfill Kenya's Vision 2030 ambitions and align national outcomes with global and regional development frameworks (Government of Kenya, 2007; UN, 2015; AU, 2015).

The foundational objective of this study was therefore to assess how renewable energy value chain dynamics interact with the performance associated with the three major economic sectors of Kenya. With insight into the interplay between renewable energy value chain dynamics and sectoral performance in Kenya, policymakers can formulate strategies to advance sustainable levels of economic growth and development in Kenya and beyond, while also paying attention to environmental sustainability.

1.2 Statement of the Problem

The three productive sectors are pivotal for Kenya's overall economic development, job creation, infrastructural growth, poverty reduction and industrialization. Despite the country's substantial renewable energy capacities, the performance of these key sectors remains constrained by persistent energy insufficiency and inefficiencies. The low sectoral performance rates are largely attributed to macroeconomic energy insufficiency arising from a mismatch between Kenya's renewable energy capacity and what is actually produced and consumed. Thus, youth unemployment remains high at 18%, while 33% of Kenyans live in abject poverty. Kenya utilizes only about 30% of its installed renewable energy capacity, with 22% of generated electricity lost in transmission-distribution. These inefficiencies manifest as frequent power blackouts, load-shedding and high energy costs, which increase production costs, discourage investment and ultimately suppress sectoral performance. On the consumption side, recurrent load-shedding and power outages highlight the unsustainable nature of Kenya's energy use, undermining the development of 24-hour economic activities. Similarly, low renewable energy ramp-up and suppressed grid penetration rates reflect misallocation, loss, misuse and inefficiencies in energy production. Despite favourable policy interventions such as feed-in tariffs and advantageous power purchase agreements, energy shortages continue to impede sectoral performance. In particular, Kenya's energy deficit is evident in its net energy imports, which account for 22.3% of total energy use, highlighting a persistent energy gap between domestic supply and demand despite substantial renewable energy capacity. This gap highlights the structural limitations in meeting sectoral energy requirements, directly constraining performance in manufacturing, services and agriculture. National development frameworks, such as Kenya's Vision 2030 and international frameworks such as the SDGs and

Africa's Agenda 2063, recognize energy as a cornerstone for sectoral performance. However, Kenya's inability to close the gap between energy demand and supply limits progress toward these objectives. Renewable energy value chain dynamics are widely recognized as key drivers of sectoral growth through reduced energy costs, improved productivity and increased investment. However, existing studies largely examine renewable energy variables in isolation rather than capturing the full energy chain from installation, generation, consumption and transmission–distribution losses in relation to sector-specific growth in manufacturing, agriculture and services. In particular, the renewable energy value chain has not been modelled jointly to establish how its interconnected value chain dynamics influence sectoral growth. In addition, transmission-distribution losses are often excluded from growth models despite their critical role in determining the availability, reliability as well as cost of usable electricity. As a result, the literature remains limited in explaining the sector-specific growth effects of renewable energy expansion and the extent to which these effects depend on system efficiency and loss reduction. This study addresses these gaps by empirically examining the full renewable energy value chain in explaining sectoral growth in Kenya.

1.3 Objectives of the Study

This study aimed to investigate the influence of renewable energy value chain dynamics on productive sector growth in Kenya.

1.3.1 Specific objectives of the study

The specific objectives of this study were to;

i. Analyze the influence of renewable energy value chain dynamics on manufacturing sector growth in Kenya.

ii. Examine the influence of renewable energy value chain dynamics on service sector growth in Kenya.

iii. Estimate the influence of renewable energy value chain dynamics on agriculture sector growth in Kenya.

1.4 Research Hypotheses

The hypotheses of this study were;

1. H_0:Renewable energy value chain dynamics do not influence manufacturing sector growth in Kenya.

H_1:Renewable energy value chain dynamics influence manufacturing sector growth in Kenya.

2. H_0: Renewable energy value chain dynamics do not influence service sector growth in Kenya.

H_1: Renewable energy value chain dynamics influence service sector growth in Kenya.

3. H_0: Renewable energy value chain dynamics do not influence agriculture sector growth in Kenya.

H_1: Renewable energy value chain dynamics influence agriculture sector growth in Kenya.

1.5 Significance of the Study

This study produced robust empirical evidence on how renewable constructs: installation, generation, consumption and transmission-distribution losses affect sectoral performance in Kenya. By quantifying how specific renewable energy indicators influence agriculture, manufacturing and services, while employing time series econometric techniques, the study addresses a key gap in the literature where sector-specific impacts remain underexplored. The findings provide practical guidance for policy planners by identifying which renewable energy variables exert the greatest influence on sectoral performance, supporting the formulation of data-driven, sector-targeted policies that enhance performance, reduce inefficiencies in the energy supply chain and optimize resource allocation. The results are expected to inform strategic prioritization of energy investments and policy reforms aligned with Kenya's development agenda and Vision 2030 goals. Government institutions such as the Ministry of Energy and EPRA can utilize these outputs to design interventions that improve grid reliability, increase renewable energy penetration and address structural constraints limiting sectoral performance. By revealing which sectors are most responsive to renewable energy inputs, the study supports the development of differentiated energy access strategies and sector-specific efficiency targets.

Methodologically, the research disaggregates renewable energy value chain dynamics into installation, generation, consumption and transmission-distribution losses rather than combining them into a single measure, reflecting both theoretical reasoning and empirical considerations. This separation allows a clearer understanding of the mechanisms through which renewable energy influences sectoral performance. Installation captures the capacity-building phase and investments in physical assets such as solar, wind and biogas facilities,

recognizing that installed capacity does not guarantee immediate availability due to commissioning delays or technical inefficiencies. Generation measures actual output and distinguishes potential capacity from actual production, while consumption reflects effective energy use, accounting for accessibility, affordability and transmission-distribution factors that determine productive capacity. Transmission-distribution losses capture inefficiencies in the energy system that reduce the energy available for sectoral production.

By modeling these components separately, the study enhances the accuracy of sector-specific elasticity estimates and strengthens the policy relevance of the findings, enabling identification of bottlenecks and targeted interventions. Academically, the research contributes methodological rigour and contextual relevance to the discourse on renewable energy and sectoral performance. Its dynamic modeling and sectoral decomposition provide a template for similar analyses in other Sub-Saharan African economies, expanding the academic frontiers of applied energy economics. Environmental economists and sustainability advocates benefit from empirical insights into how the adoption of renewable energy contributes to low-carbon growth. By linking sectoral performance outcomes to renewable energy value chain dynamics, the study provides an evidence-based foundation for integrated policies that balance economic advancement with ecological stewardship, a contribution pivotal to Kenya's Vision 2030 and SDGs 7 and 8. This approach ensures that the research generates actionable, policy-relevant insights tailored to Kenya's developmental needs while enriching the broader knowledge on sustainable energy transitions in emerging economies.

1.6 Scope of the Study

Geographically, this study was conducted in Kenya, Africa. It focused on greening Kenya's sectoral performance agenda. Its key purpose was to assess the influence of renewable energy value chain dynamics, which are renewable energy installation, renewable energy generation, renewable energy consumption and net renewable energy transmission-distribution losses on the manufacturing, service and agriculture sectors in Kenya. This will aid in informing sector-specific policies. The three sectors were chosen as they are the main sectors in the economy where energy is expended. Capital, labour and the respective non-renewable energy dynamics entered the model as controls. This research work considered the period 1980-2024. This is the period that came just after the 1970s worldwide oil crisis that ushered in a period of dependency on renewable energy solutions as opposed to nonrenewable energy resources.

Methodologically, the study applied a correlational design and made use of the ARDL-ECM frameworks to assess both the long-term and short-term relationships existing amongst the parameters. They helped determine the presence, intensity and sign of any existing associations. The research was grounded on the neoclassical Solow-Swan model and treated all four renewable energy constructs: installation, generation, consumption and losses as inputs that complement traditional growth factors such as gross capital formation and labour. The data is log-transformed.

This study focused on the three productive sectors in which previous studies have focused on either one sector or the general economy. Further, the renewable energy value chain dynamics are captured through installation, generation, consumption and transmission-distribution losses disaggregated data to understand the interconnectedness between the three main economic sectors: agriculture, services and manufacturing and the four renewable energy value chain dynamics under focus. Precisely assigning renewable energy installations and generation to each sector is challenging, as tracking its generation and installation at the micro-level is complex, but is feasible on the consumption part. Therefore, it relied on previously collected longitudinal renewable energy statistics for the period spanning from 1980 to 2024 to navigate these challenges.

Renewable energy value chain dynamics drive sectoral growth by lowering energy costs, enhancing productivity and stimulating investment and domestic value chains, especially where supported by strong infrastructure and institutions.

Evidence examining renewable energy installation, generation or consumption in isolation rather than jointly linking the full renewable energy chain to sectoral growth across manufacturing, agriculture and services. Additionally, net transmission–distribution losses are rarely incorporated into sectoral growth models despite their central role in determining usable electricity, prices and reliability, which can condition the growth effects of renewables.

In the literature, evidence base is strongest for renewable energy consumption and aggregate growth, but weaker for modelling the renewable energy chain end-to-end: installation, generation, consumption and net transmission-distribution losses against sectoral value added in manufacturing, agriculture and services. Thus, current literature offers limited guidance on the sector-specific growth payoffs of renewable expansion and on whether these payoffs depend critically on reducing transmission–distribution losses and improving the efficiency with which renewable generation reaches productive users.

1.7 Theoretical Framework

The neoclassical Solow-Swan theoretical growth framework, as put forward by Robert Solow, was exploited. It relates shifts in output to comparable shifts in population, adjustments in the savings rate and the corresponding technological advancements. This growth model is the pillar of contemporary economic theory. The model as advanced and posited by Robert Solow, harbours a myriad of assumptions: the presence of full employment, the existence of wage and price flexibility, the neutrality of technological advancement, the substitutability of labour and capital, consistency of the savings ratio, consistency of returns to scale and the production of a single composite good. This study employed robust econometric techniques and empirical validation to account for these assumptions.

According to this model, the association between the stated sectors and the renewable energy constructs is represented by the general Cobb-Douglas equation 1.1, in which the renewable energy constructs enter the model as inputs into the economy's productive processes.

$$Y_t = A_t K_t^{\alpha} L_t^{1-\alpha} \ldots\ldots\ldots\ldots (1.1)$$

Where;

Y_t is sectoral output at time t;

K_t is capital at time t;

L_t is labour at time t;

A_t is total factor productivity at time t;

α is capital elasticity of output.

To incorporate renewable energy value chain dynamics while preserving constant returns to scale, renewable energy does not enter the model as an additional scale input. Instead, renewable energy affects output through total factor productivity by enhancing efficiency, reliability and technological performance of the production process. The production function is therefore expressed as;

$$Y_t = A_t RE_t K_t^{\alpha} L_t^{1-\alpha} \ldots\ldots\ldots\ldots (1.2)$$

Where;

Y_t is sectoral output at time t;

K_t is capital at time t;

L_t is labour at time t;

RE_t is renewable energy input, that is, installation, generation, consumption and transmission-distribution losses, at time t;
α is the output elasticity of output, representing the contribution of capital to sectoral output (0< α < 1).

This general formulation is then specialized in a unified model for the three objectives as follows:

$$Y_{jt} = A. RET_t^{\alpha_1}. REG_t^{\alpha_2}. REC_t^{\alpha_3}. RNTL_t^{\alpha_4}. K_t^{\alpha_5}. L_t^{\alpha_6} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.\dots\dots\dots\dots. (1.3)$$

Where;

Y_{jt} is the output of a productive sector j at time *t;*

RET_t is renewable energy installation at time t;

REC_t is renewable energy generation at time t;

REC_t is renewable energy consumption at time t;

$RNTL_t$ is renewable energy net transmission-distribution losses at time t;

K_t is capital input at time t;

L_t is labour input at time t;

A is the total factor productivity capturing efficiency gains from energy variables at time t;

For sectoral representation, output Y_{jt} is alternatively defined as:

$$Y_{jt} = \begin{pmatrix} MVA_t \\ SER_t \\ AVA_t \end{pmatrix} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.\dots\dots\dots\dots.. (1.4)$$

Where *MAN* denotes manufacturing sector output, SER denotes services sector output and AGR denotes agricultural sector output.
In this study, the Solow–Swan framework provides a structure for examining how renewable energy value chain dynamics influence sectoral growth in Kenya without violating its core theoretical assumptions. Capital and labour remain the fundamental scale inputs, while renewable energy installation, generation, consumption and losses operate through productivity effects captured by total factor productivity. This formulation ensures theoretical

consistency, preserves constant returns to scale and provides a defensible bridge between growth theory and the study's empirical analysis.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter presents a synthesis of theoretical and empirical studies, a synthesis of the unexplored areas and gaps that need addressing, as well as other research gaps in the renewable energy-sectoral performance dynamics**.**

2.2 Theoretical Literature Review

Sectoral performance has been explained through various theoretical frameworks that link capital, labour, technology and natural resources to output and sectoral performance. Understanding the role of renewable energy constructs in Kenya's sectoral performance requires situating it within these frameworks. The following discussion reviews four key growth theories: The Harrod-Domar model, the neoclassical Solow-Swan model, endogenous growth models and growth models with natural resources, providing the foundation for analyzing how renewable energy installation, generation, consumption and transmission-distribution losses influence sectoral growth.

2.2.1 The Harrod-Domar model

The Harrod-Domar framework utilizes a Keynesian perspective on economic development as advanced by Sir Roy Harrod in 1939 in his essay, "The Dynamic Theory," and Russian-American economist Evsey Domar in 1946 through his contributions in his work titled, "Capital Expansion, Rate of Growth and Employment". The Harrod-Domar model became a foundational framework that helped understand economic growth by focusing on the link that exists between savings, investment and the extent of growth in the economic sectors. The model harbours assumptions such as: full employment, constant capital-output ratio and that savings are a fixed proportion of income.

This model, therefore, attempts to link how investments in renewable energy installation, generation, consumption and transmission-distribution losses influence sectoral growth. This model therefore fronts energy as a fundamental catalyst of sectoral growth and therefore advocates for interventions geared towards promoting sustainable energy policy interventions that will guarantee the growth of the sectors.

This model suggests economic growth; in this case, the performance of the three sectors, manufacturing, service and agriculture, could be determined by computing the ratio of savings to the capital-output ratio.

$$Y = \frac{s}{k} \quad \text{(2.1)}$$

Substituting sectoral growth and the renewable energy value chain dynamics yields;

$$Y_t = \frac{S_t}{K/Y_t} = f(RET_t, REG_t, REC_t, RNTL_t) \quad \text{(2.2)}$$

Where;

Y_t is output of a sector at time *t;*

S_t is savings allocated to a sector and time *t*;

K/Y_t is the capital-output ratio of a sector;

REC_t is renewable energy installation at time t;

REG_t is renewable energy generation at time t;

REC_t is renewable energy consumption at time t;

$RNTL_t$ is renewable energy transmission-distribution losses at time t.

This formulation embeds renewable energy as a key determinant of sectoral performance, aligning with the Harrod-Domar notion that investment drives performance. Each energy variable captures a distinct dimension of energy infrastructure, supply, utilization and efficiency, thereby allowing the model to estimate their combined and individual impacts on manufacturing, service and agricultural performance.

The Harrod-Domar growth model connotes that sectoral growth increases with renewable energy investments and efficiency but decreases with the level of the corresponding capital-output ratio. The types of growth identified under the Harrod-Domar model are warranted growth, actual growth and natural growth. The warranted type of growth suggests that the rate of growth does not continue perpetually. The actual type of growth refers to the annual

augmentation of national GDP, while the natural type of growth occurs when a nation's economic structure reaches a state of full employment.

The model possesses several weaknesses, among them the unrealistic assumptions of the constancy of the capital-output ratios and fixed savings rates. The model does not take into account technological advancements and changes and is static. Neoclassical economists also argue that the Harrod-Domar model leads to unstable solutions. As alternative modelists, neoclassical economists advocate for the use of the Solow-Swan framework. This justifies why this piece of knowledge made use of the more robust Solow-Swan framework, as these weaknesses are also inherent in the other stated theories.

The Harrod-Domar model, which highlights the significance of investment in stimulating economic and sectoral growth, offers a useful theoretical mechanism for examining the existing linkages between the energy constructs and sectoral growth and development in Kenya. According to this model, economic and sectoral growth is driven by savings rate and capital efficiency, emphasizing the importance of investments in capital-intensive sectors, such as energy, to boost overall and sectoral growth. Renewable energy, a vital form of capital, is very critical in driving growth by cutting energy costs and ensuring a more reliable supply. Specifically, backing renewable energy ventures and generation is capable of promoting growth across the three key sectors by enhancing energy efficiency, lowering operational expenses and reducing the overdependence on depletable non-renewable energy resources. This aligns with the core principles of the Harrod-Domar model, which suggests that continuous sectoral growth is achievable through the accumulation of capital and improved efficiency, with green energy sources playing a pivotal role (Domar, 1946). Thus, this model serves as a valuable tool for assessing how renewable energy investments and developments influence sectoral growth, directly addressing the first objective of this study.

2.2.2 The Endogenous Growth Model

According to this model, as put forward by Paul Romer in 1986, the level of aggregate output is dependent upon the level of human capital, knowledge, labour, technology and innovation that are considered internal or endogenous factors and variables. The corresponding production function can be written as;

$$Y = F(K_t N_t A_t) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots .. (2.3)$$

In line with the endogenous growth model, the level of sectoral output can be expressed as a function of capital, labour and technology-enhancing factors, including renewable energy value chain dynamics. In this renewable energy-sectoral growth study, sectoral growth is dependent on internal factors such as renewable energy investments and installations and efficiency and can be modelled as;

$$Y_t = F\left(K_t, L_t RET_t REG_{t,} REC_t RNTL_t\right) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . \ldots \ldots \ldots \ldots \ldots \ldots (2.4)$$

Where;

Y_t is output of a sector at time *t;*

K_t is the capital of a sector at time *t*;

L_t is the labour of a sector at time *t*;

RET_t is renewable energy installation at time t;

REG_t is renewable energy generation at time t;

REC_t is renewable energy consumption at time t;

$RNTL_t$ is renewable energy transmission-distribution losses at time t.

This specification highlights the renewable energy value chain dynamics as endogenous drivers of sectoral growth, consistent with Romer's proposition, where investment in energy infrastructure, efficient utilization and management of losses contribute to knowledge, productivity and long-term growth of the manufacturing, service and agriculture sectors.

In the endogenous growth framework, sectoral growth in manufacturing, services and agriculture is influenced by internal factors, with renewable energy constructs explicitly included. Renewable energy installation, generation, consumption and transmission-distribution losses enter the model as key inputs. Elasticities measure the relative impact of each energy construct, allowing the model to capture how investments, effective use and efficiency of energy resources drive sustained sectoral growth in Kenya.

The Endogenous growth model assumes that human resources represent the sole factor required in the acquisition of knowledge. The model further states that economic output is generated through the utilization of both physical and human capitals. It highlights that growth is an internal phenomenon and remains unaffected by external influences.

Romer (1986) is premised on the fact that technological advancement serves to offset diminishing returns of capital that greatly inhibit growth. This model, with its specifications, may, therefore, not be appropriate in establishing the influence of the renewable value chain dynamics on sectoral growth.

This model is interlinked with the energy-economic growth nexus as posited by Ozturk (2010) through the roles played by human capital, knowledge, labour, technology and innovation in accelerating economic growth. This therefore, implies that investment in innovations in energy technologies and alternative energy cultures is a prerequisite for the attainment of achieving economic and sectoral growth and productivity while at the same time curbing environmental challenges.

This model also harbours the unrealistic assumption of constant returns to scale, in a world where diminishing growth can occur due to other external factors. This assumption is mitigated by including more variables in the model so that the non-constancy of the returns to scale can be explained by the other key and control variables, such as capital and labour.

This model emphasizes that economic and sectoral growth and productivity are propelled by internal factors, for instance, technology, human resources and invention and can therefore be directly linked to investments in renewable energy in Kenya. In this theoretical framework, investments in renewable energy value chain dynamics serve not only to increase immediate energy availability but also to foster innovation and efficiency across key sectors of the economy. Renewable energy encourages sectoral growth by lowering long-term power costs and creating incentives for power-efficient practices. As a result, these investments lead to sustainable growth by enhancing sectoral growth, reducing energy losses in the value chain and promoting innovation within industries. In line with the endogenous growth model, renewable energy becomes a critical engine of growth, where policies and investments in energy infrastructure stimulate long-term economic development through continuous improvements in growth and technology(Romer,1990). This model can be useful in addressing the installations dynamics and energy investment issues associated with the objectives since they are internal factors.

2.2.3 Growth Models with Natural Resources

According to Stern (2004), economic and sectoral growth can take different dimensions when natural resources are available for use, alongside capital and labour. These resources are part of the process, assuming they can be substituted and supported by technological progress. Stern

(2010) argues that factors like the ability to substitute different inputs are key in determining how sustainable growth can be. By incorporating natural resources into the model, the elasticity of substitution between labour and capital helps to explain how the different inputs interact with each other.

Growth models with natural resources aim to incorporate the role of natural resources into economic growth theories. These models recognize the importance of natural resources in productive activities. Several strategies are employed in incorporating natural resources into growth models: Resource-Based Growth Models, Endogenous Growth Theory with Natural Resources, Resource Curse Models, Sustainable Development Models and Dynamic Stochastic General Equilibrium Models with Resources.

Resource-Based Growth Models, propounded by Jeffrey Sachs and Andrew Warner and other economists in the 1990s expound on the key contribution of natural resources as a critical enabler of economic advancement. In this context, the resource-based growth models focus on how the different energy constructs, that is, installation, generation, consumption and their imminent depletion contribute to or inhibit macroeconomic growth. This is largely due to the fact that power is pivotal in the production process and its scarcity functions as a constraint on overall economic growth. They typically focus on the elicitation, production and shipment of these primary natural resources and seek to establish how these activities contribute to overall economic growth. However, they also acknowledge the potential risks associated with the overreliance on finite resources and the associated challenges of managing resource revenues optimally. The fear of attrition of fossil-based sources serves as the primary reason this study opted to explore renewable energies as an alternative due to their replenishment capabilities.

The Endogenous Growth Theory with Natural Resources, propounded in the 1980s and 1990s by Paul Romer and other environmental economists, emphasizes the critical role played by internal factors within the economy such as technological growth, accumulation of human capital and institutional quality by enabling long-run economic development and not the external factors. Some extensions of endogenous growth models incorporate natural resources by considering how investments in resource exploration, extraction efficiency and environmental sustainability can affect growth rates over time. This model attempts to draw a focus on technological advancements, knowledge and the existing policies as far as shaping economic growth in a country is concerned.

Resource Curse Models, also known as the paradox of plenty, explore the idea that countries rich in natural resources may face slower economic growth, increased corruption and higher political instability compared to nations with fewer resources. These models examine the unintended negative effects of resource abundance on a country's economic and political development. The model was put forward by Paul Collier and Anke Hoeffler in 2001(Collier and Hoeffler, 2000, 2005). Resource curse models seek to explain the mechanisms by which natural resource endowments can lead to undesired economic outcomes such as some specific diseases, sectoral imbalances, environmental degradation, corruption and social conflicts, which are the negative externalities of a well-endowed resource sector. This model attempts to advocate for good governance, having quality and responsive institutions and economic diversification as the interventions for mitigating the shortcomings associated with resource curses. Responsible economies should also invest in human capital development, adopt diversification measures and incorporate mechanisms that foster transparency and accountability.

Sustainable Development Models, propounded by Amartya Sen, the Brundtland Commission and other economists in the 1980s, seek to optimize resource use over the long term, drawing a wedge between economic and sectoral growth and environmental sustainability and the social well-being of a population. These models are known to adopt frameworks that champion environmental sustainability and social equity. They may incorporate factors such as renewable resource management, pollution control and investments in alternative energy sources. They advocate for the management of resources, including energy resources, in a way that sustains the current demands without compromising on future requirements. This is why this study adopted renewable energies. These models advocate for shifts from traditional resource-intensive growth patterns to less intensive practices that are sustainable, both in the short and long runs, while also ensuring environmental sustainability.

Dynamic Stochastic General Equilibrium Models(DSGE) with Resources are macroeconomic models that capture the existing relationships between households, firms and government within an economy. The model was put forward by Finn Kydland and Edward Prescott and other economists in the 1980s. These models provide a structure for the realization of how fluctuations in the availability of resources, which includes energy resources, impact the process of economic growth. Some DSGE models include natural resources as a factor of production, allowing researchers to analyze the impacts of shocks, fluctuations in the prices of resources and resource policy interventions on overall economic and sectoral dynamics, such

as consumption. These models aid policymakers in designing interventions that draw a balance between the country's desire for economic growth and sustainable resource management by incorporating constraints and stochastic elements that help in navigating the shortcomings of energy dependency and the imminent energy resource depletions.

These models, though, have the capability of addressing renewable energy installation, generation, consumption and losses, possess several shortcomings. These models have simplistic assumptions; they assume a linear relationship between resource endowments and economic growth. They therefore ignore other factors, such as institutional factors that may affect economic growth other than resource endowments. This study addressed this shortcoming by having more control variables and the error term to account for the other impacts on sectoral growth that are not attributable to renewable energy installation, generation, consumption and net transmission-distribution losses.

The basic model showing how renewable energy constructs relate to sectoral growth can be described as:

$$g = \delta + \beta REI_t^{\alpha} Eff_t^{\theta} NR_t^{\gamma} \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \text{ (2.5)}$$

Therefore, the basic model showing how renewable energy constructs relate to sectoral growth can be described as;

$$g_t = \delta + \beta_1 RET_t^{\alpha} + \beta_2 REG_t^{\theta} + \beta_3 REC_t^{\emptyset} + \beta_4 RET_t^{\gamma} + \varepsilon_t \dots \dots \dots \dots \dots \dots \dots .. \dots \dots \dots \dots . \text{ (2.6)}$$

Where;

g_t is the growth rate of a sector *(*manufacturing, service and agriculture) at time *t*;

δ is a constant term representing baseline growth independent of the energy value chain dynamics;

RET_t is renewable energy installation at time t;

REG_t is renewable energy generation at time t;

REC_t is renewable energy consumption at time t;

$RNTL_t$ is renewable energy transmission-distribution losses at time t.

β_1,β_2, β_3, β_4 are the elasticities capturing the responsiveness of sectoral growth to the respective renewable energy components.

α , θ, $\emptyset$ and γ are the components representing the intensity of each energy input's effect.

ε_t is the stoschastic term capturing the unobserved factors affecting sectoral growth.

This formulation incorporates renewable energy installation, generation, consumption and transmission-distribution losses critical inputs within the sectoral production function, aligning with natural resource-based growth theory. The model also allows for non-linear effects and input intensities, reflecting the reality that energy inputs may have diminishing or increasing marginal impacts on manufacturing, service and agricultural growth. By including the error term, the model accounts for all other influences on sectoral growth not captured by renewable energy constructs, addressing limitations in classical resource-based models.

Growth models with natural resources provide a suitable framework for integrating renewable energy value chain dynamics into sectoral growth analysis. In this study, renewable energy installation, generation, consumption and transmission-distribution losses are treated as productive natural resource inputs alongside gross capital formation and labour in explaining growth in manufacturing, services and agriculture. Consistent with the arguments of David Stern, these models allow for substitutability between inputs and emphasize the role of technology and efficiency in sustaining growth. By incorporating efficiency, losses and energy use across the value chain, the framework aligns with endogenous and sustainable development extensions that stress innovation, institutional quality and long-run resource management, as highlighted by Paul Romer and Amartya Sen. This integrated approach enables a comprehensive assessment of how renewable energy as a natural resource shapes sectoral growth outcomes in Kenya while accounting for sustainability and efficiency considerations.

Therefore, growth models with natural resources provide insights into the complex relationships between resource endowments, renewable energy in this case, sectoral growth and sustainable development. They offer policymakers valuable tools for designing strategies to manage natural resources effectively and promote inclusive and environmentally sustainable growth.

2.3.4 The Neoclassical Solow Swan Growth Theory

This framework was exploited by this study in a bid to explore any existing association between sectoral growth and the stated renewable energy value chain dynamics. This model was posited by Robert Solow in 1956 and it depicts a continuous output model that seeks to relate the

economic output with amounts of capital as well as labour used in the process of production. It assumes that capital, coupled with labour can conveniently substitute for one another.

Solow based his model on the Cobb-Douglas framework, which is a framework that seeks to relate production levels to changes in factors such as population growth, saving rates and technological advancement. The Solow-Swan model has become a fundamental pillar of modern economic theory, operating under several key principles, including constant returns to scale, an unchanging rate of saving, neutral technological progress, the ability to substitute capital for labour, full employment and flexible wages and prices, with the economy producing a single composite good. Despite its influence, the model is not without limitations, including its relatively simplified treatment of capital and the assumption that capital can be readily substituted and repurposed across productive activities.

To address these limitations and align the framework with the objectives of this study, capital and labour were incorporated as control variables, while renewable energy was introduced as an additional productive input. The Solow-Swan framework is appropriate for this study because it provides a theoretical basis for explaining how changes in productive inputs and technological conditions influence long-run output and productivity. In particular, renewable energy value chain dynamics represent a technological and productive transformation that can affect the availability, reliability and efficiency of energy used in production. Its incorporation into the production framework therefore makes it possible to examine whether changes in renewable energy installation, generation, consumption and losses are associated with changes in productive-sector output while controlling for conventional production factors such as capital and labour.

The Cobb-Douglas specification is particularly suitable because it provides a tractable production-function framework for examining the relationship between output and multiple productive inputs and allows the contribution of each input to be estimated while holding other factors constant. This is consistent with the objective of this study, which examines the influence of different stages of the renewable energy value chain dynamics on the growth of the manufacturing, services and agricultural sectors in Kenya. The framework also accommodates the disaggregation of renewable energy into installation, generation, consumption and transmission-distribution losses, thereby enabling the study to move beyond treating renewable energy as a single undifferentiated input. Gross capital formation and labour

are retained as control variables because productive-sector growth is not determined by energy alone. Thus, the extended framework provides a coherent theoretical foundation for investigating how renewable energy value chain dynamics interact with conventional factors of production to influence sectoral output in Kenya.

This study's Solow-Swan Cobb-Douglas production framework, which has been extended to incorporate renewable energy as a complementary productive input, reflecting its role in enhancing productive efficiency across sectors, can be specified as;

$$Y_t = A_t RE_t K_t^{\alpha} L_t^{1-\alpha} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2.7)$$

Now assuming this is a log-log framework,

α is a value between zero and one,

α and (1-α) represent the output elasticities of capital and labour,

α is the output elasticity in relation to capital, *K*, implying that a unit or a 1% rise in capital results in a *α%* rise in output, *Y*, when labour, *L*, is held constant.

A is the total factor productivity that captures the efficiency and technological progress of the production process by reflecting the portion of output not explained by capital or labour inputs.

1-α is the elasticity of output with respect to labour, implying that a 1% increment in Labour, L, leads to a (1-α) % increment in output, *Y*, while holding Capital, *K*, constant.

RE represents renewable energy input, that is, renewable energy installation, renewable energy generation, renewable energy consumption and renewable energy transmission-distribution losses.

In this study, the neoclassical Solow-Swan model is adapted to include renewable energy variables as additional inputs influencing sectoral outputs: manufacturing *(MAN)*, services *(SVA)* and agriculture *(AGR)*. Capital *(GCF)* and labour *(L)* remain the traditional inputs, while renewable energy installation *(RET)*, generation *(REG)*, consumption *(REC)* and transmission-distribution losses *(RNTL)* enter the production function as complementary factors that enhance productivity and efficiency.

This model suggests that energy is a critical component in the production process, highlighting its vital role in capital accumulation and driving economic and sectoral growth. This relationship emphasizes the importance of sound and sustainable energy policy interventions and innovations in realizing enhanced economic growth while also minimizing negative environmental externalities.

The sum of the elasticities always equals one. This indicates that the returns to scale are always constant, meaning that in the event both capital and labour increase by the same proportion, the output will rise by the same proportion and vice versa.

An evaluation of this literature points to the fact that input substitution and technological innovation possess the potential of separating economic advancement derived from the renewables, alongside other essential inputs. Neoclassical theorists primarily focused on examining institutional arrangements that promote an enduring economic progress rather than emphasizing technological frameworks.

This model, however, does not take into account the various environmental concerns in the relationship between the inputs and outputs. This study mitigated this by employing control variables that were able to take into account the other factors affecting economic and sectoral growth, other than the main variables. This model, therefore, has the capability of addressing all the three study objectives simultaneously.

In this Solow-Swan framework, the renewable energy variables, that is, installation, generation, consumption and losses, are incorporated as sector-specific productive inputs that complement the standard factors of production. Renewable energy installation captures the physical infrastructure that underpins energy use, renewable energy generation represents the flow of energy available for production**,** consumption reflects the extent to which this energy is actually applied in driving sectoral output, while the renewable energy losses account for the efficiency gaps that reduce productive energy use. In this way, renewable energy value chain dynamics are introduced into the model alongside gross capital formation and labour, thereby allowing their independent influence on growth to be assessed without treating them as mere duplicates of the capital control variable.

Although several growth theories offer insights into the energy–growth nexus, the neoclassical Solow–Swan framework is most suitable for analyzing renewable energy–sectoral growth dynamics in Kenya. The Harrod–Domar model, while foundational in emphasizing the role of

investment, is constrained by its restrictive assumptions of fixed capital–output ratios and constant savings rates, which limit its empirical applicability in economies characterized by structural change and energy transitions (Harrod, 1939; Domar, 1946). Endogenous growth models extend this analysis by internalizing technological progress and human capital accumulation; however, their heavy reliance on unobservable knowledge variables and strong scale assumptions reduces their tractability for sector-specific empirical analysis involving measurable energy inputs (Romer, 1986). Similarly, growth models with natural resources highlight the importance of resource endowments and substitution possibilities but often overemphasize abundance and depletion effects, while offering limited guidance on isolating the distinct roles of energy installation, generation, consumption and losses across productive sectors (Stern, 2004; Sachs & Warner, 1995). On the other hand, the Solow–Swan framework provides a flexible and empirically robust structure that accommodates multiple inputs, allows for diminishing returns and permits technological efficiency to evolve over time, making it well-suited for integrating renewable energy constructs alongside capital and labour in sectoral growth analysis (Solow, 1956; Swan, 1956).

2.3 Empirical Literature Review

Although the study objectives are formulated around the manufacturing, services and agricultural sectors, the empirical literature is organized according to the four renewable energy value chain dynamics; installation, generation, consumption as well as transmission-distribution losses. This approach is deliberate because the existing literature is largely fragmented across individual renewable energy dynamics, with many studies examining their relationship with aggregate economic growth rather than examining the renewable energy value chain as an integrated system. Organizing the review strictly by sector would therefore require separating studies that examine the same renewable energy value chain dynamic across different sectors and would exclude or unnecessarily fragment the substantial body of literature on aggregate economic growth. Reviewing the literature by renewable energy value chain dynamics instead allows the study to systematically synthesize the evidence on each component of the value chain and subsequently examine its implications for manufacturing, services and agriculture. In particular, the review identified no empirical study that evaluates installation, generation, consumption and transmission-distribution losses jointly as a composite renewable energy value-chain framework and examines their influence on the three productive sectors. This integrated treatment is also important empirically because the four dynamics are interconnected; modelling them jointly allows the effect of each dynamic to be

estimated while accounting for the other components, rather than treating each relationship in isolation. The novelty of this study therefore lies in bringing these previously fragmented dynamics together within a single renewable energy transition framework and empirically establishing how the composite value chain influences Kenya's manufacturing, services and agricultural sectors.

2.3.1 Relationship Between Renewable Energy Installation and Sectoral Growth

An input-output analysis by Dell'Anna (2021) in Italy, in an effort to ascertain any existing interconnections between green jobs and the growth of the economy, established that investing in green installations led to overall productivity. Dell'Anna (2021) sought to explore the investment potential in Italy's energy production industry using Input-Output analysis. The study exploited data for the period 1990-2016. However, this body of knowledge is from a more advanced economic setting and its findings might not be replicable in Kenya, thereby justifying why this study had to be conducted, using Kenya-specific data sets.

Wei *et al.* (2022), a study done to establish the contribution of Foreign Direct Investment in stimulating economic growth in renewable energy development, established that investing in renewable energy installations greatly reduced greenhouse discharges in China. Wei *et al.* (2022) exploited the ARDL with a pooled mean group and data from 30 Chinese provinces for the period 2000-2019 and established that renewable energy financing and installation accelerated the process of economic growth. The study, however, is from an economy with different energy endowments compared to Kenya and, therefore, cannot be replicated in Kenya, hence the need for this study.

Sohail et al. (2025) examined the relationship between SDG 7 energy indicators and economic growth in Pakistan using annual data from 1990 to 2023. The study employed the ARDL approach to establish short and long run relationships and further applied Random Forests and Generalized Additive Models as robustness checks. The findings indicated that access to electricity, energy intensity, installed renewable energy capacity and international financial inflows significantly influenced economic growth in the long run. Granger causality tests further revealed both bidirectional and unidirectional causal relationships among the energy indicators and economic growth. While the study provides recent evidence that renewable energy installation can contribute to economic growth, its analysis treats installed renewable energy capacity as one component of a broader set of SDG 7 indicators and focuses on the aggregate economy of Pakistan. Thus, it does not establish whether the expansion of renewable

energy capacity produces differentiated growth effects across individual productive sectors. This leaves an important gap regarding the sector-specific growth implications of renewable energy installation, particularly in developing economies such as Kenya, where agriculture, manufacturing and services have different energy requirements and production structures. This study addresses this gap by disaggregating the analysis to the sectoral level and examining the dynamic relationship between renewable energy installation and growth in Kenya.

García-Riazuelo et al. (2025) examined the long-term socioeconomic impacts of renewable energy deployment in rural regions of Europe using a novel annual dataset of renewable-energy installed capacity across European Nomenclature of Territorial Units for Statistics Level 2 (NUTS2) regions. The dataset covered multiple decades and included wind and photovoltaic installations, allowing the study to capture both the scale and growth of renewable-energy infrastructure. Using the Synthetic Control Method, the study evaluated the intra and interregional socioeconomic effects of renewable energy installations and found that renewable energy infrastructure can create opportunities for economic growth, employment generation and population recovery in rural regions. However, the study focused on European rural regions and renewable energy installation, leaving limited evidence on how renewable energy deployment affects specific productive sectors in developing economies. This study addresses this gap by examining the effects of renewable energy installation, generation, consumption and transmission-distribution losses on manufacturing, services and agricultural growth in Kenya using annual time-series data and a dynamic ARDL approach.

According to Brunner and Schwegman (2022), in its quest to determine the connection between commercial wind power installations and economic growth, established that wind installations led to a significant rise in the GDP of the US. The study exploited an event-study difference-in-differences instrumental variable approach, exploiting the plausibly exogenous timing and location of wind energy installations and cross-county variation in average wind speeds to identify the causal impacts of wind energy. These installations were also responsible for the increased incomes of the locals. The study adopted commercial wind energy data for the period 1995-2018. The study, however, treated economic growth as an aggregate; hence, the need to do a study in Kenya that establishes sectoral growth. This study also suffers from the problem of the aggregation of the impacts. In its effort to mitigate this shortcoming, this study sought to delve into the specific impacts of the different renewable energy installations on specific sector productivities.

Bulut and Menegaki (2020) sought to investigate how solar energy influences overall economic performance and growth across different sectors in the world's top 10 economies by installing solar capacities in those countries. It found that the solar energy coefficient was not significant within the model and saw no causal linkage existing between solar installations in relation to the economic well-being of China, the USA, Japan, Germany, Italy, India, the UK, France, Australia and Spain. It made use of panel cointegration analysis and data spanning from 1999 to 2015. However, the study harboured the challenges of aggregation of economic growth data. This body of knowledge aimed at mitigating this shortcoming through disaggregating the economic sectors as well as aggregating renewable energy as a composite variable. This study sought to disaggregate renewable energy into its specific components as well as break down the economic sectors into manufacturing, service and agricultural sectors so as to facilitate the formulation of sector-specific and energy-type specific policy interventions.

According to Idzikowski and Cierlicki (2021), investment in solar energy installations led to accelerated overall economic activity in Poland. The study sought to establish the economic and energy performance of renewable energy installations. The study also postulated that investment in solar energy has a payback period of 9 years. Poland and Kenya are at different stages economically hence; the research outputs are unlikely applicable to the Kenyan situation. Poland is also a country with different natural and energy resource endowments compared to Kenya. The political and policy dynamics in Poland might also not be replicable in Kenya. This current research seeks to address this limitation by conducting the study specifically in Kenya. the study also considered only 9 years, which is a period that may not yield theoretically plausible outcomes sufficient for policy making. The adoption of the payback method is also an inferior tool for establishing any existing associations between investments in Solar energy and sectoral growth and productivity, as it only considers the time value of investments but ignores important components such as the magnitudes of the associations. These shortfalls, together with the problem of aggregation, were addressed by this study by employing an adequate data set of 46 years using a robust ARDL model in Kenya.

Zahoor et al. (2022) examined the effects of clean energy investment and financial development on environmental sustainability and economic growth in China using annual data covering the period 1970–2016. The study incorporated manufacturing value added and urbanization as moderating variables and employed structural-break unit root tests, fully modified least squares, dynamic least squares and robust least squares to estimate the long-run relationships. The findings showed that clean energy investment was negatively associated

with CO_2 emissions and ecological footprint while being positively associated with economic growth. On the other hand, financial development, manufacturing value added and urbanization were positively associated with both economic growth and environmental degradation. The study therefore demonstrated that clean energy investment can contribute to economic growth while simultaneously improving environmental sustainability. Its use of structural-break tests and multiple long-run estimation techniques strengthens the robustness of its findings. However, the study focused on aggregate clean energy investment rather than specific dimensions of the renewable energy value chain and did not examine renewable energy installation, generation, consumption or transmission and distribution losses separately. Moreover, its analysis was confined to China and aggregate economic growth, leaving the effects of renewable energy dynamics on individual productive sectors in other developing economies insufficiently addressed. This study extends this literature by disaggregating renewable energy transition dynamics and examining their effects on the growth of manufacturing, services and agriculture sectors in Kenya.

Shafiei *et al*. (2014) aimed at assessing the influence green energy deployments had on overall economic well-being amongst the Organization for Economic Co-operation and Development (OECD) economies using data for the period 1980-2011. It made use of the panel co-integration and the Granger to assess the existing associations between green installations and sectoral growth. Its findings indicated a strong positive sustained linkage existing across the study parameters, thereby suggesting investments in green energy solutions to a large extent contributed towards economic growth in OECD countries. Nevertheless, the study's focus on long-term effects and its restriction to OECD countries limits the applicability of the findings to short-term dynamics and to developing economies, where the economic context might differ significantly. This study exploited the robust ARDL that is capable of determining linkages both over the temporary and extended periods. Kenya, not being in the same advantageous position compared to the OECD economies, might not benefit from Shafiei *et al*. (2014) as the dynamics could differ, hence the need for this study.

Ahmad and Zhao (2018), research undertaken in China and exploring data for 2001-2016 and exploiting the mean group estimator introduced in the second-generation common correlated effects approach to establish the causal linkage between energy investment and general economic growth identified a substantial as well as a bilateral kind of association existing between investments in renewables' installations and growth. Ahmad and Zhao (2018), however, established that the effect of investing in green installations on economic growth on

green power investments is greater than that of renewable energy installations on economic productivity in over 38 provinces in China. Therefore, there exists a feedback relationship amongst the variables. The study, however, suffers from the problem of aggregation as economic growth was not disaggregated into specific sectors. This study aimed to mitigate this shortcoming by exploiting sector-specific and energy-type specific data for ease of policy formulation.

Dirma et al. (2024) examined the impact of renewable energy development on economic growth in the European Union using panel data and comparative and theoretical analysis. Using a dataset covering EU countries, the study found that renewable energy development does not hinder long-term economic growth but can promote it through investment, technological advancement and employment creation. However, the study focused on aggregate economic growth and did not distinguish between renewable energy installation, generation and consumption or examine sector-specific effects. This study addresses these gaps by using annual Kenyan time series data to examine the effects of renewable energy installation, generation, consumption and transmission-distribution losses on manufacturing, services and agricultural growth using a dynamic ARDL approach.

Li and Li (2020) explores the interplay existing between energy investments and installations, economic productivity and growth of China's carbon effluents, employing a spatial Durbin framework for their comparative empirical examination. The research by Li and Li (2020) covers a period leading up to its publication, offering insights into how energy investments impact both economic performance and carbon emissions across different regions in China. The findings established explicitly that investing in renewable energy installations and alternatives positively influences overall economics and sectoral growth while also affecting carbon emissions, highlighting the complex interactions between these variables. The study, however, is limited to China and countries that are as advanced as China and may therefore not be replicable in Kenya. This is why this study sought to explicitly conduct the study in Kenya due to difficulties in replicating Li and Li (2020) in the Kenyan case.

On the interactions between renewable energy installations and how they impact sectoral performance, much of the reviewed literature, apart from being from regions and economies at different stages of development, suffers from the problem of first-degree aggregation of the impacts. The existing body of knowledge regarded economic growth as a composite variable and, hence, it was difficult to apportion the effects to the specific sectors within the

economy. This renders policy implementation cumbersome because of the ambiguously wide and generalized nature of the study outcomes and directives. This body of knowledge addressed this shortcoming by employing disaggregated statistics to unravel the specific sector and energy type-specific relations to ease policy formulation. Renewable energy was disaggregated into its various components, such as hydro and geothermal, while the economy was disaggregated into manufacturing, service and agriculture sectors.

2.3.2 Relationship Between Renewable Energy Generation and Sectoral Growth

While exploiting the GMM method of analysis in order to ascertain the impact both renewable and non-renewable energy had on economic growth, Atems and Hotaling (2018) established that both depletable and non-depletable energy generations had positive impacts on the economy, while power losses within the cycle occurring during power transmission-distribution were found to negatively impact economic and sectoral growth. The study considered cross-panel data from 174 nations during the 1980-2012 period. The study, however, did not delve into sectoral growth. The study also suffers from the problem of aggregation; as renewable energy was treated as an aggregate. This study mitigated this by disaggregating renewable energy into the various renewable energy forms and examining their effect on sectoral growth in Kenya.

According to Oyeleke and Akinlo (2020), a study conducted in Nigeria using the ECM and considering data spanning from 1980 to 2017 in a bid to uncover any existing linkage between the generation of power and overall economic growth, established a cointegrating kind of association existing between the generation of renewable energy and economic advancement. It further established that gas energy solutions, tangible assets and the prevailing rates of interest are very critical as far as accelerating long-term economic and sectoral growth is concerned. Nevertheless, the study established that hydroelectric power generation significantly led to economic growth. However, the study did not delve into sectoral growth but rather treated economic growth as an aggregate. This research aimed to address these challenges by not only exploring disaggregated data but also exploring other renewable energy generations besides hydroelectric power.

Yoo and Kim (2006) worked to clarify the existing linkage between electricity generation and the growth of Indonesia's economy. It found a one-way kind of association spanning from economic growth all the way. There was no evidence of a two-way kind of response. The study adopted data for the period 1971-2002. Yoo and Kim (2006), however, is from a country with

different natural resources and energy endowments compared to Kenya. The study also suffers from the problem of first-degree aggregation, as electricity was not disaggregated into its various forms. This study mitigated this by isolating the specific effects of each of the major renewable energy forms.

Jeon (2022) sought to establish the energy generation-economic productivity in 47 US states, considering data spanning from 1999 to 2017 exploiting the two-step GMM model. The research established that renewable energy generation led to significant positive economic growth rates. On the other hand, nonrenewable energy generation hampered economic growth. However, the US is in an advantageous position economically compared to Kenya. This study was necessary to clear this geographical ambiguity.

Fang et al. (2025) examined the relationship between renewable energy generation and economic growth across 30 provinces in China using data for 2007–2019. Employing an integrated decomposition analysis and a refined Laspeyres index decomposition approach, the study investigated the spatial-temporal drivers of renewable energy generation and its causal relationship with economic growth. The findings showed that electricity-generation structure, carbon emissions and electrification levels were important drivers of renewable energy generation, while changes in generation efficiency constrained renewable energy development. The study further found that efficiency and structural effects, rather than investment effects, dominated the relationship between renewable energy generation and economic growth. However, the study focused on Chinese provinces and examined the generation–growth relationship largely through decomposition and aggregate economic activity, leaving limited evidence on how renewable energy generation affects specific productive sectors in developing countries. This study addresses this gap by examining the effect of renewable energy generation on manufacturing, services and agricultural growth in Kenya using annual time-series data and a dynamic ARDL framework.

Adedoyin *et al*. (2020) sought to assess any existing association between energy generation and environmental-economic advancement consequences amongst the EU member states over 1992-2014 using the GMM methodology. It was established that a 1% rise in the level of nonrenewable generation dampened pollutant emissions. The findings from this body of knowledge indicate that a 1% rise in the level of generation of renewables causes a corresponding rise in carbon effluents in the USA by 0.04% and Central and Eastern European economies by 0.02% correspondingly, but reduces carbon effluents by 0.02% in the New

Member States. Both representations of New Member States and the Commonwealth Environmental Kuznets Curve of Independent States align with the U-shape of the Environmental Kuznets Curve's inverted U premise. Nevertheless, findings of the representations from Central and Eastern European economies invalidate the Environmental Kuznets Curve proposition. This proposes ecological outcomes of steady economic growth in jurisdictions in Central and Eastern Europe limit emissions growth. Therefore, the study observed that there were differences in degradation levels within members of the blocs. Adedoyin *et al*. (2020), however, relies on evidence drawn from a highly industrialized economy. This phenomenon provided the much-needed rationale for extending the analysis to Kenya.

Phiri and Nyoni (2023) examined the relationship between clean electricity generation and economic growth in South Africa using annual data for 1985–2021. Employing wavelet coherence analysis, the study compared the growth effects of aggregated and disaggregated clean and dirty electricity sources. The findings showed that renewable sources, particularly solar, wind, biomass and hydropower, had greater potential to enhance economic growth across both short and long run frequencies, while the growth effects of coal, oil and gas weakened over time. However, the study focused on South Africa and examined aggregate economic growth rather than sector-specific growth. This study extends this evidence by examining the effect of renewable electricity generation on manufacturing, services and agricultural growth in Kenya using a dynamic ARDL framework.

Ohler and Fetters (2014) examined the causal relationship between renewable electricity generation and economic growth across 20 OECD countries over the period 1990–2008. Using a panel ECM, the study disaggregated renewable electricity generation into biomass, geothermal, hydroelectricity, solar, waste and wind sources. The findings revealed a bidirectional relationship between aggregate renewable electricity generation and real GDP, indicating that renewable electricity generation and economic growth reinforce each other. At the individual energy-source level, biomass, hydroelectricity, waste and wind exhibited positive long-run relationships with GDP, while hydroelectricity and waste generation showed short-run bidirectional causality with GDP growth. The study further found that biomass, hydroelectricity and waste electricity generation had the largest long-run effects on real GDP. By accounting for structural breaks and cross-sectional dependence, the study provided a more robust assessment of the renewable electricity–growth relationship. However, the study focused on electricity generation and did not examine other stages of the renewable energy

value chain, particularly transmission and distribution losses. It also concentrated on aggregate GDP across OECD countries rather than sector-specific outcomes in developing economies. The present study extends this literature by examining renewable energy transition dynamics across installation, generation, consumption and transmission-distribution losses and their implications for manufacturing, services and agriculture sector growth in Kenya.

Bayraktutan et al. (2011) examined the relationship between renewable electricity generation and economic growth in OECD countries over the period 1980–2007 using panel-data analysis. The study found a positive long-run relationship between renewable electricity generation and economic growth, indicating that greater generation from renewable sources contributes to long-term economic performance. The study also established bidirectional causality between renewable electricity generation and economic growth, suggesting that renewable electricity generation supports economic growth while economic expansion simultaneously stimulates renewable electricity generation. The study is relevant in demonstrating the contribution of renewable electricity to economic performance and the existence of feedback effects between energy development and growth. However, it focused specifically on renewable electricity generation and did not examine other stages of the renewable energy value chain, particularly renewable energy installation, consumption, or transmission and distribution losses. It also examined aggregate economic growth across OECD countries rather than the performance of individual productive sectors in a developing-country context. This study extends this literature by disaggregating renewable energy transition dynamics into installation, generation, consumption and transmission-distribution losses and examining their effects on manufacturing, services and agriculture sector growth in Kenya.

Ullah *et al.* (2024), while exploring the association between hydroelectric power, economic advancement and financial performance amongst 10 hydro-power generating economies for the period 1990-2020, established that the generation of hydropower accelerates both monetary development and economic growth in an economy. Furthermore, a bidirectional relationship was established amongst all three variables, thereby conforming to the feedback hypothesis. The study exploited the panel-corrected standard errors technique, the Augmented Mean Group method, the Westerlund-Edgerton LM bootstrap and the Dumitrescu-Hurlin panel causality framework. It, however, suffers from the reliance on a broad, cross-country analysis, which might not explain well the country-specific factors and variations in hydroelectric power's impact. This study was conducted with Kenya-specific data, therefore ensuring easy

replicability with countries with similar energy situations. This study also factored in other renewable energy constructs beyond hydroelectric energy.

Hdom (2019) in its quest to investigate the relationship that exists between carbon effluents, power production from fossil fuels and renewable sources, along economic advancement across nations in South America over the 1980–2010 time period, used the ARDL approach on panel data to analyze how different types of power production influence economic advancement and carbon effluents, established significant interactions between these variables; showing how shifts in energy generation mix can impact both economic performance and environmental outcomes. This study established that renewable energy generation possessed an adverse effect on carbon effluents over time and a constructive influence on economic activity. These South American economies explored by Hdom (2019) have the advantage of renewable energy resource endowments and different economic and social organizations compared to Kenya and therefore, the study could not be replicated in Kenya, hence the justification for conducting this study.

Onyeisi *et al*. (2016) investigated how power generation capacity influenced economic growth in Nigeria between 1980 and 2015. They modelled Real GDP as a function of power generation capacity in kilowatts, gross capital formation and unemployment. Using co-integration tests, the VECM and Granger causality tests, it established a stable connection over time connecting the outcome and predictor indicators, confirmed by two co-integrating equations. This suggests that their findings apply to long-term policy decisions. However, the VECM revealed that power generation had an insignificant effect on Real GDP. Therefore, the study concluded that the absence of any direct connection between power generation capacity and Nigeria's economic growth over the research duration. It recommended improving the transparency of power sector policies and reforms and ensuring full budget implementation with stronger legislative oversight to mitigate and fight the consequences of corruption activities in Nigeria. While the study's context in Nigeria offers insights for replication in Kenya, it's important to consider that Nigeria's position as a leading oil producer could make its energy generation and consumption patterns different from those of energy-importing countries like Kenya, the same needed to be replicated in Kenya.

Just like renewable energy installations, the majority of the reviewed literature that attempts to account for the interaction existing between renewable energy value chain dynamics and sectoral advancement does not provide ways of determining sector-specific impacts, hence

making policy formulation economic, social and political transformation when contrasted with Kenya and hence their findings might not be replicable in the Kenyan context. Some of the reviewed studies are also from economies at a similar economic orientation as Kenya but they possess varied resource endowments compared to Kenya. This dynamic makes it difficult to replicate the findings as what may have worked in such economies might not suit Kenya. Some of the reviewed studies also explored methodologies that could not allow them to assess both the signs and intensities of the connections. The research aimed to address these shortcomings by employing Kenya-specific data and the robust ARDL to help determine both the immediate and extended associations that exist connecting renewable energy components with sectoral development and efficiency.

2.3.3 Relationship between Renewable Energy Consumption and Sectoral Growth

Numerous empirical investigations have been conducted to examine the connection between renewable energy consumption and sectoral growth. According to Ozturk (2010), the energy-economic growth nexus can be summarized into: growth hypothesis, neutrality hypothesis, feedback hypothesis as well as the conservation hypothesis.

The growth hypothesis suggests a one-way causal link where power drives economic growth, underscoring the essential role of energy in stimulating development. It argues that limited access to adequate energy resources creates barriers to economic advancement. It therefore implies that renewable energy value chain dynamics positively impact the level of sectoral growth. The conservation hypothesis focuses on energy-saving measures and efficiency improvements that do not compromise economic growth. This perspective highlights that those economies, in this case, the three sectors of the economy, may become less reliant on energy-intensive practices as they grow, suggesting mutual independence linking sectoral growth and the usage of energy. It supports interventions to improve energy accessibility as a road to sustainable growth. The feedback hypothesis portrays energy as well as the upturn in economic performance as mutually dependent and has a two-way kind of association, reinforcing their mutual relationship. This hypothesis implies a reciprocal kind of linkage between the green clean energy constructs and sectoral growth. On the other hand, the neutrality hypothesis, on the other hand, posits that there is no meaningful causal connection existing between energy and economic growth, implying that any observed association between sectoral growth and renewables is coincidental rather than indicative of a deliberate relationship.

Pao and Fu (2013) examined the causal relationships between renewable and non-renewable energy consumption and economic growth in Brazil using annual data for the period 1980–2010. Using the VECM framework, the study found a long-run equilibrium relationship among real GDP, labour, capital and the different forms of energy consumption. The findings revealed a unidirectional causality running from non-hydroelectric renewable energy consumption to economic growth, while total renewable energy consumption and economic growth exhibited bidirectional causality. These findings suggest that renewable energy consumption plays an important role in supporting economic growth in Brazil, while economic growth can, in turn, stimulate the consumption of renewable energy. The strength of the study lies in its disaggregation of renewable energy consumption and its examination of the direction of causality between energy consumption and economic growth. However, its focus on Brazil limits the extent to which its findings can be generalized to other emerging economies with different economic, institutional and energy-system characteristics. This study therefore extends this line of inquiry to Kenya by examining how different dimensions of renewable energy dynamics, including installation, generation, consumption and transmission-distribution losses, interact with the performance of the manufacturing, services and agriculture sectors.

Studies that are in consonance with the growth hypothesis within the energy-economic growth framework suggest that the utilization of green energies significantly affects industrial production. An example is the assertion by Obange *et al.* (2013) that examined the influence of renewable energy possessed on Kenya's manufacturing sector growth. It found a two-way Granger causality existing between the utilization of electricity and manufacturing, observed over both the short and long-run periods. Drawing on historical time series data over the 1970-2010-time period, it highlighted the existence of a relationship but did not delve into the magnitude or intensity of these effects. On the other hand, this study employed advanced analytical methods to not only confirm the presence of such relationships but also to analyze the direction, strength and scale of the impacts and interactions.

Apergis and Payne (2014) aimed to unravel the factors influencing the usage of green sources of energy per capita across a set of seven Central American countries spanning the period 1980-2010. Using dynamic panel data models, the analysis revealed a long-term cointegrated relationship between Per-person energy usage, inflation-adjusted GDP per individual and individual carbon dioxide emissions, real coal prices and real oil prices, with positive and statistically significant coefficients. However, the study acknowledged that the effects differed

based on the countries' levels of development and energy infrastructure. One of the weaknesses of this study lies in the inconsistency in the soundness of the dataset across the nations, which could potentially impact the reliability of the results. This study comes in handy to address the shortcomings of Apergis and Payne (2014) by exploring sufficient and econometrically plausible data sets from the Energy Information Administration(EIA) and World Development Indicators(WDI) for the period 1980-2024.

Sadorsky (2009) pioneered research exploring the link between green energy uptake and economic development, focusing on the G7 nations, namely, Canada, France, Germany, Italy, Japan, the UK and the US. Using panel data from 1980 to 2005, the study applied a panel cointegration method to assess how green energy production impacts economic growth. Results of the exploration indicated that, over the long term, real average economic output per person and as well as CO_2 per head, were significant contributors to individual green energy utilization. However, it also noted that the effect was stronger in countries with more developed financial markets, suggesting that financial development could enhance the benefits derived from renewable energy generation. A notable limitation of the study was its relatively short data span, which might fail to reflect extended temporal patterns, thereby potentially making the econometric conclusions less robust. This study exploited a sufficient 1980-2024 data set.

Bowden and Payne (2010) conducted a study focusing on the US, utilizing a historical dataset for the 1949-2006 period. The Toda-Yamamoto framework was exploited to explore how renewable energy utilization relates to economic performance. Their long-run causality tests indicated no range-type causal link existed between commercial and industrial uptake of green energy and constant-price GDP. However, bidirectional Granger causality was observed between non-renewable energy use in the commercial and household sectors and inflation-adjusted GDP. Additionally, findings showed unidirectional causality from residential renewable power utilization and industrial use of fossil fuels in relation to inflation-adjusted GDP. A key limitation of this study is its exclusive focus on the United States(US), which may restrict the applicability of the findings to other regions with differing energy frameworks. This study sought to bridge this geographical barrier.

Ototo and Nzai (2021) using annual time series data from 1980-2019 while exploiting the multivariate time series model and incorporating relevant time-series diagnostics, including cointegration test, to assess both the contemporaneous as well as the delayed impacts of the utilization of both the sustainable and fossil-based energy on Kenya’s manufacturing and

industrial sector performance in Kenya, found a bidirectional kind of interaction observed in the usage of green alternatives as well as the performance associated with the manufacturing and industrial sector. However, the study advocates for the exploitation of energy-efficient infrastructure to check energy losses within the value chain. The study, apart from exploiting a less robust analysis technique, did little to establish the magnitudes of the associations. The ARDL methodology that this study exploited was capable of examining both the short and long-term magnitudes associated with the suspected associations.

Hoang *et al.* (2020), an investigation that sought to evaluate the existing connection between renewable energy usage and industrial performance across the US for the period spanning from 1981 to 2018, by employing the Granger causality test, found a significant co-movement exists amongst the variables. It adopted the usage of fossil-based energy as well as crude oil prices as control variables. Hoang *et al.* (2020), however, did little to assess the magnitudes of the associations. The US is in a diverse stage economically and hence its findings aren't replicable to Kenya. This study, thus, sought to clear the ambiguity regarding the sign, direction and magnitudes of the interactions.

Kasae (2014), in its effort to establish energy efficiency in Kenya's manufacturing sector using baseline and current data in Kenya, established that efficiency in the energy value chain possessed a significant influence on manufacturing productivity and growth. The study focused on a sample of 70 manufacturing firms from a total of 735 listed by the Kenya Association of Manufacturers, with a particular emphasis on firms that had previously conducted energy audits. The study utilized regression analysis. This implies that energy consumption led to increased manufacturing growth. However, the study treated energy consumption as an aggregate. According to Kasae (2014), the study is also not definitive as findings from other companies were not in consonance with these results. The study also notes that this finding was inconclusive, as certain companies exhibited weak correlation coefficients for the variables at both baseline and current levels, indicating the necessity for further investigation. This study helped clear the ambiguity, besides also incorporating other sectors of the economy, not just the manufacturing sector.

Onuonga *et al.* (2008), in its quest to determine the existing relationship between the two key parameters, did an econometric assessment to determine the kind of association existing between manufacturing output and energy use in Kenya. The study adopted a trans-logarithmic function to assess total factor specifications involving fuel substitutions. It utilized data from

1970 to 2005. The findings indicated that manufacturing growth was linked to an increased use of various inputs, including different types of energy. However, Onuonga *et al.* (2008) failed to accurately single out the specific effect on the manufacturing sector given the fact that manufacturing activities were being influenced by many other factors in the model. This study not only singled out the specific impacts of renewable energy constructs on the manufacturing sector but also sought to clear the same ambiguity about the farming and service industries.

Forkuoh and Li (2015) sought to unravel the nexus between electricity insecurity and the growth of small manufacturing and industrial plants in Ghana. It sought to determine the impact attributable to power outages on the effectiveness of the manufacturing plants. Forkuoh and Li (2015) highlighted a positive connection existing between energy efficiency, usage and the growth of the firms. The study also established that the use of backup generators during power outages led to increased costs of production, thereby suppressing production. By the use of mixed methods of study and SPSS output, the study, that solely focused on the Asafo market established that power availability and reliability affected the performance of the manufacturing plants. The study, however, is from an economy with different natural and energy resource endowments compared to Kenya. This study was specific to Kenya and economies with similar resource endowments, economic conditions and political climate as Kenya.

Grainger and Zhang (2017) sought to evaluate the influence of electricity shortages on the operational effectiveness associated with Pakistan's industrial enterprises. It exploited a cross-sectional regression analysis using firm-level data, where the natural logarithms of firm revenues and value-added were regressed on indices measuring the duration and frequency of electricity shortages, while controlling for labour costs, raw material costs, fixed assets, total electricity costs and sector-specific dynamics in a bid to estimate the influence power outages had on firm productivity. It considered the performance of 4,500 firms for the period 2010-2011. Electricity shortages were measured as the number of hours that the power blackouts lasted. The study established that a 10% rise in the number of outage hours led to a 0.14% decline in firms' revenues and a 0.36% decline in value-added. This implied that it positively influenced manufacturing output and growth. However, the study ignored the intensity of the associations. This study aided in not only determining the presence but will also help determine the sign, direction and intensities of the associations.

Guja-Huseynli (2023) aimed to assess how energy use relates to the export of products and services within Italy's service sector in Mediterranean countries, using data from 1997 to 2021.It made use of the panel data analysis method, which examines the relationship between the variables by evaluating data across multiple cross-sections and time periods to capture both individual and overall effects. Findings of the study suggested that a 1% increment in energy use brought about a 27% boost associated with the commercial services sector. The study, apart from being from a non-representative population compared to Kenya, treated energy consumption as an aggregate variable and by not isolating the effect of the renewables from the non-renewables. This study also sought to cure this geographical and economic stage-related heterogeneity.

Ásványi et al. (2017) conducted a comprehensive literature review on the role of renewable energy in the tourism industry, with particular attention to its application within the service sector, accommodation facilities and tourism destinations. Using content analysis of existing research, the study examined the extent to which renewable energy contributes to energy efficiency, sustainability and cost reduction in tourism. The review found that renewable energy has considerable potential to support the sustainability and operational efficiency of tourism-related activities, although research on its application in the industry was still at an early stage. The study also identified examples of renewable energy best practices across different destinations and emphasized the need for further research on the influence of renewable energy across the various components of tourism. However, the study was qualitative and review-based rather than an econometric analysis and therefore did not empirically estimate the effect of renewable energy on service-sector growth. Moreover, it focused specifically on tourism rather than the broader services sector and did not examine different stages of the renewable energy value chain, including installation, generation, consumption or transmission-distribution losses. This study extends this literature by empirically examining how renewable energy transition dynamics influence the growth of the broader services sector, alongside manufacturing and agriculture in Kenya.

Sadorsky (2011), in its quest to determine the relationship between the existing linkage between financial sector growth and energy use across frontier markets in Central and Eastern Europe, established a significant correlation existing between financial sector growth and energy uptake. It exploited a dynamic panel dataset framework with the GMM regression in order to ascertain the influence of financial development on power uptake in nine Central and Eastern European frontier economies over the period 1996 to 2006. A methodological

limitation is that, while the panel GMM approach addresses endogeneity, the relatively short time span and limited number of countries may reduce the generalizability of the findings. In addition to the fact that the research is from more advanced economies compared to Kenya, the study has issues of first-degree aggregation. The study considered energy consumption as a collective measure, but it became clear that a more detailed breakdown was necessary to analyze the specific impact of each form of renewable energy separately. This study will also employ a robust methodology that will enable it to determine the magnitudes of the associations, an attribute that is lacking in Sadorsky (2011). This study, apart from seeking to mitigate the geographical heterogeneities, employed robust econometric tools to aid in also determining the magnitudes of the interactions.

Farhani and Ozturk (2015), in its analysis of the Cause-and-effect relationship existing between Carbon effluents, real GDP, energy usage, financial services development, market openness and the level of urban development in Tunisia over the 1971-2012 period, established a significant cause-and-effect association flowing from energy usage and trade openness and financial services. The study employed the auto-regressive distributed lag bounds procedure to assess long-term equilibrium linkages and employed an ECM framework to evaluate both immediate and extended interactions among carbon emissions, economic growth, energy use, financial sector development, trade integration as well as urban growth in the Tunisian context, thus providing a robust framework for capturing both immediate and lagged effects among the variables. Despite coming from an African economy that could be replicated in Kenya, the study viewed energy utilization as one aggregated construct. The magnitudes as well as the intensities of the associations were also not established. The ARDL framework that was adopted by this study mitigated this problem.

Ali *et al*. (2015), in its investigation of how financial development intertwines with overall economic growth, energy costs and energy usage in Nigeria, using a dataset for the 1972-2011 period while exploiting the ARDL framework, found a nexus existing between energy uptake and the evolution of financial services. This set of findings is in consonance with the study results of Chang (2015), research that was done in 53 counties using data for the period 1999-2008. The studies, however, harbours the problem of first-degree aggregation as energy consumption was treated as an aggregate variable and not disaggregated into renewable and nonrenewable to establish their individual effects. The studies also did not determine the magnitudes of the association between the variables. This study exploited sector-specific data to alleviate the problem of aggregating the impacts.

Some empirical studies, such as Obange (2019), while exploring data for the period 1970-2010 using the VECM in Kenya, found that renewable energy consumption exerted a substantial influence on Kenya's agriculture sector performance. This effect was one-way. The study detected a unilateral relationship, indicating that energy use drives agricultural growth. However, it did not consider other factors that may influence the level of agricultural growth apart from energy consumption. This study exploited other variables in the model, as energy consumption cannot be the only factor influencing the growth of the sectors. This study also adopted capital, labour and conventional power constructs as control variables. Other factors affecting sectoral growth, other than the listed factors, were taken care of by the error term in this study.

Sartbayeva *et al.* (2023) aimed at unraveling the existing linkage between the uptake of green energy solutions, economic growth and the agriculture-linked industrial sector in Kazakhstan, utilizing a dataset for the period 1991-2021. Evidence from the research pointed to a one-way relationship where agricultural production influences renewable energy consumption. The study employed hierarchical regression analysis for its assessment. However, despite being conducted in a more developed economy, the research did not quantify the strength of the relationship. The study, just like many studies in this area, suffers from the problem of aggregation of the impacts, hence making policymaking a nullity. This study addressed this shortcoming by disaggregating energy consumption into the various amounts of renewable energy consumed. This study is disaggregated to mitigate this.

Liang *et al.* (2020), in Kazakhstan, while analyzing the consumption patterns of livestock products in Kazakhstan over the periods 1992–2000 and 2000–2013 using both qualitative and quantitative methods, made use of descriptive statistics, trend analysis and assessment of socio-economic and ecological factors to analyze the characteristics and determinants of milk, meat and egg consumption across different regions. The study established the existence of a feedback cause-and-effect linkage between green energy utilization and agricultural sector productivity. This is because animal feeds need energy to prepare and in turn, the increased the uptake of green energies, which means more yields derived from agriculture. Liang et al. (2020), however, offered no information on the intensity of the linkages. ARDL-ECM methodologies employed by this study are critical in determining not only the magnitudes and direction but also the speeds of adjustment, too.

Smagulova *et al.* (2023), also in Kazakhstan aimed to explore the interplay between the two variables by coming up with an econometric model intended to determine the connection existing between electricity generation and usage and digital farms on increased output from the agricultural industry. The study made use of annual data from 2017 to 2021 and employed multivariate regression modeling to examine the influence of determinants such as electricity production and the total number of digital agricultural farms on gross agricultural output in Kazakhstan. The methodology is robust but may be limited by the relatively short five-year period. Smagulova *et al.* (2023) concluded that these variables possessed a significant influence on agricultural production. However, the research focuses on a comparatively advanced economy. This was needed to conduct this study in Kenya, as Kazakhstan may not reflect the Kenyan situation politically, economically, climate-wise and also in terms of energy resources endowments. The time period under consideration was also too short and therefore violated some basic econometric guidelines. This investigation tackled the identified deficiency by exploiting a sufficient dataset of the period 1980-2024.

Zou (2022) aimed at investigating the connection between agricultural productivity and China's power utilization, utilizing the Toda Yamagoto tests along with data from 1953 to 2020. Evidence from the research pointed to a reciprocal interplay between energy use and crop-livestock yields. However, the study considered energy consumption as a single aggregate variable, highlighting the need for further analysis by separating renewable and nonrenewable energy sources to understand their individual effects. Additionally, given that China is at a different level of economic development than Kenya, conducting a similar study in Kenya was necessary to account for regional differences.

Ahmad *et al.* (2019), in its quest to assess the linkage uptake of renewables, economic growth as well as environmental dynamics in China, while exploiting the 1981-2996 dataset, found no evidence of Granger-causality linking energy uptake and the performance of the agricultural sector and suggested that the stringent energy-saving mechanisms employed in the agricultural industry will not ultimately adversely affect agricultural activities. However, a Granger-causality bidirectional relationship was found to exist between the variables across eastern and western China in the period 1990-2008, but no causal relationship in central China. The differences were attributed to economic and social differences amongst the regions (Hu *et al.*,2011). The study, however, harbours the inadequacies of aggregation, which is one of the critical shortcomings of existing literature that this study sought to mitigate.

Zhang *et al.* (2019), a study done in China using the data for the period 1996-2015 to ascertain the interplay between carbon emissions, energy utilization and agricultural sector growth, established that there was a one-way Granger causality flowing from the usage of energy by agricultural processes to agricultural progress and advancement. The study opined that energy consumption is a major enabler of agricultural growth. However, the study also harbours the shortcomings of treating energy consumption as an aggregate, a gap this study sought to mitigate.

Similarly, Tiwari *et al*. (2021), in a bid to investigate the linkage between electricity usage and overall growth of the economic sectors, drawing on data covering the period 1960-2015, established a unidirectional long-run heterogeneous panel causality flowing from electricity usage to agricultural productivity in India. The inquiry also established a causality flowing from industrial growth to electricity usage. The study, besides being silent on the intensities of the association, cannot be replicated in Kenya due to the social and economic differences between Kenya and India, hence the need for this study.

According to Martinho (2016), a study done in 12 EU member states' farms using data for the period 1989-2009 and for the years 2004–2012 to establish the resourcefulness as well as growth implications of renewable energy use within the agriculture sector across Europe, found that energy consumption negatively affected agricultural growth. It was therefore concluded that though the relationship was significant, it was negative. The data under consideration was analyzed using the different econometric techniques; the GMM and frameworks drawing from the Kaldor developments. The study, however, did not solely focus on renewable energy but instead dealt with energy consumption as a variable. Aggregation of the impacts is one of the gaps of past knowledge that this study sought to address.

Apergis and Payne (2010) examine the relationship between renewable energy consumption and economic growth for a panel of 20 OECD countries over the period 1985–2005, employing a multivariate framework with panel cointegration and ECM models. Findings reveal a long-run equilibrium relationship between real GDP, renewable energy consumption, gross fixed capital formation and the labour force, with all coefficients positive and statistically significant, while Granger-causality tests indicate bidirectional causality between renewable energy consumption and economic growth in both the short- and long-run. This study provides robust cross-country evidence for developed economies; however, it is limited by its focus on OECD countries, the relatively short time series and the absence of sector-specific analysis or

consideration of energy losses and infrastructure efficiency, which may influence the energy–growth nexus. This study addresses these gaps by examining renewable consumption, Kenya's three main sectors: manufacturing, services and agriculture, capturing the full energy value chain and providing insights into both short- and long-run sectoral effects, thereby complementing and extending the OECD-focused findings of Apergis and Payne (2010) in a developing country context.

Apergis and Payne (2012) examined the relationship between renewable and non-renewable energy consumption and economic growth using a multivariate panel of 80 countries over the period 1990–2007. The study employed the Pedroni heterogeneous panel cointegration test to establish the existence of a long-run equilibrium relationship among real GDP, renewable energy consumption, non-renewable energy consumption, gross fixed capital formation and labour force. The results showed that both renewable and non-renewable energy consumption had positive and statistically significant effects on real GDP in the long run, with relatively similar elasticity estimates. Further, the panel ECM revealed bidirectional causality between renewable energy consumption and economic growth, as well as between non-renewable energy consumption and economic growth, in both the short and long run. The study also found bidirectional short-run causality between renewable and non-renewable energy consumption, suggesting substitutability between the two energy sources. The study is valuable for demonstrating the importance of renewable energy consumption in supporting economic growth across a broad international sample and for establishing feedback relationships between energy consumption and economic performance. However, its focus was on energy consumption rather than the physical infrastructure and efficiency of the electricity supply chain. The study did not examine transmission-distribution losses or distinguish between electricity generated and electricity lost before reaching consumers. This study extends the literature by shifting attention from renewable energy consumption to renewable-energy transition dynamics, including transmission-distribution losses and by examining their implications for the growth of manufacturing, services and agriculture sectors in Kenya.

Inglesi-Lotz (2016) investigates the impact of renewable energy consumption on economic growth using panel data techniques for OECD countries over the period 1990–2010. The study examines both the absolute volume of renewable energy consumed and its share in the total energy mix, providing a quantitative assessment of its contribution to economic welfare. The results show that renewable energy consumption has a positive and statistically significant effect on economic growth, indicating that integrating renewable energy into national energy

portfolios supports not only environmental sustainability but also economic development. However, the study is limited to developed economies and does not consider sector-specific effects or the role of energy losses, which may influence growth outcomes in countries with different energy access and infrastructure conditions. This study addresses these gaps by analyzing renewable energy consumption across Kenya's main economic sectors: manufacturing, services and agriculture, thereby capturing both short- and long-run effects on sectoral economic growth.

Chen *et al*. (2020) examines the relationship between renewable energy consumption and economic growth using a threshold model for 103 countries over the period 1995–2015. The study establishes that the effect of renewable energy consumption on economic growth is context-dependent: for developing countries, it is positive and significant only when renewable energy use exceeds a certain threshold, while consumption below this threshold produces a negative effect. For developed countries, renewable energy consumption has no significant impact on growth, whereas OECD countries exhibit a positive and linear relationship. These findings demonstrate that the economic benefits of renewable energy consumption are sensitive to both the level of adoption and the development status of a country. However, the study does not explore sectoral-level effects, which are crucial for understanding how energy consumption translates into growth of the specific sectors. This study addresses this gap by analyzing renewable energy consumption within Kenya's key economic sectors: manufacturing, services and agriculture, thus capturing both short- and long-run effects on sectoral economic growth and providing insights into how sector-specific consumption patterns contribute to overall economic development.

There are conflicting results in the renewable energy-sectoral performance nexus literature. The mixed and conflicting sets of findings are largely owing to the exploitation of varied datasets, heterogeneity across countries in terms of the varying climatic conditions and the performance of the economy at the time the studies were being undertaken. The problem of mixed results is one of the pertinent justifications for this study, as it also aimed at clearing the ambiguity around renewable energy and sectoral growth. The use of robust tools of analysis also went a long way in providing reliable and meaningful policy recommendations that are devoid of the ambiguities surrounding the problem of mixed results and inconsistent findings from the available literature.

2.3.4 Relationship between net Renewable Energy Transmission-Distribution losses and Sectoral Growth

According to Xue and Wang (2021), that sought to unravel the linkage between electricity shortages and the performance of the manufacturing sector, established that electricity losses in the value chain greatly negatively impacted China's economic growth in a survey using 1673 manufacturing firms. It sought to investigate the influence electricity shortages had on the productivity of Chinese manufacturing firms, with particular attention to how firms respond through self-generation, research and development, adoption of licensed technology and reliance on temporary workers. Using firm-level data from the World Bank Enterprise Survey covering the 1,673 manufacturing firms for the fiscal year 2011 and surveyed in 2012 across 25 Chinese cities. The study applied econometric models to examine both the determinants of firm responses to electricity shortages and the extent to which these responses mitigate productivity losses. The study vouched for the investment in intensive research in green energy solutions to reduce energy losses and shortages. The study, however, is from a country that is different from Kenya economically; hence, its findings could not be replicated in Kenya.

Bhattacharya *et al.* (2016) aimed at unearthing any existing association between uptake of green solutions and economic productivity across 38 nations, both advanced and emerging, using data for the period 1991-2012. It employed panel cointegration and tests for Granger causality, revealing the existence of a prolonged positive association, with more pronounced effects being observed across the developed countries, indicating that renewable energy usage can significantly accelerate economic growth and productivity. It also advocates for the exploitation of power-efficient infrastructure to achieve economic growth. The study, however, included developed economies in its study and therefore its findings cannot be entirely representative of the Kenyan energy situation, hence the justification of why this study had to be carried out.

Adom *et al.* (2018) focused on Africa, using data from 30 countries between 1988 and 2014 to source and determine the convergence and impacts of energy efficiency within the African continent. It employed the stochastic fixed effect, true fixed effect and the Kumbhakar-Heshmati tests and data of twenty-two economies. It was established that the continent's energy efficiency challenges are structural, while convergence in energy efficiency was found to be conditional. Their stochastic frontier analysis found that improving energy efficiency, including reducing transmission losses, significantly contributed to sustainable economic

advancement, especially within countries possessing massive renewable energy investments. The study also postulates that energy intensity may not be the appropriate measure of energy efficiency. This study did not just dwell on energy intensity, but also addressed issues of the sign, magnitude and direction of the intensities into sharper focus.

Henry et al. (2021) investigated the effect of electric power deficits on sectoral economic growth in Nigeria, with electric power transmission and distribution losses used as a proxy for electric power deficit. Using annual time-series data covering 1981–2017 and the Autoregressive ARDL model, the study examined the effects of power losses on agricultural and industrial real gross domestic product. The findings revealed that a 1% increase in electric power transmission and distribution losses reduced agricultural output by approximately 3% in the long run, although the effect was insignificant in the short run. However, transmission-distribution losses had no statistically significant effect on industrial output. The study demonstrates that inefficiencies in the electricity supply chain can constrain sectoral productive performance, particularly in agriculture. Its strength lies in disaggregating economic growth into sector-specific outcomes rather than relying solely on aggregate GDP. However, the study focused on Nigeria and treated transmission-distribution losses as a general measure of electric power deficit, without distinguishing losses associated with renewable energy. Moreover, its sectoral analysis was limited to agriculture and industry, leaving the services sector unexplored. This study addresses these gaps by examining renewable energy value chain dynamics and their implications for the growth of manufacturing, services and agriculture sectors in Kenya.

Adams *et al.* (2020) examined the impact of the electrical energy lost in the course of transmission-distribution on the economy within South Africa's economic landscape. It sought to investigate the kind of association existing between power transmission as well as distribution losses and development in South Africa over the period 1971–2014, making use of the ARDL alongside the ECM frameworks to capture both the transient and enduring dynamics. It sought to establish whether inefficiencies in the energy sector, measured through transmission and distribution losses, could be a hindrance to sustainable economic performance in the South African context. It was established that huge electricity losses negatively impacted economic growth, suggesting that reducing these losses could enhance economic performance. The study's limitations include potential data inaccuracies and the challenge of isolating the specific effects of transmission-distribution losses from other economic factors. The results highlight the importance of improving the efficiency of electrical power infrastructure to

accelerate economic growth in the South African economy. This study sought to mitigate these shortcomings by exploiting a sufficient data set and also sought to disaggregate and isolate the impacts of transmission-distribution dynamics.

The study by Costa-Campi et al. (2018) utilizes a real-world hourly dataset from the Spanish electricity system covering the period 2011 to 2013 to examine the economic impact of electricity losses. Employing an econometric modelling framework that distinguishes between transmission and distribution losses while incorporating both consumption patterns and generation technologies, the study is situated within the context of Spain, a developed economy with high renewable energy penetration. The findings indicate that electricity losses constitute a significant economic cost, accounting for a considerable proportion of total energy supplied and leading to increased electricity prices, reduced consumer surplus and overall welfare losses. The study further establishes that peak demand accelerates losses due to network congestion, while the effect of distributed generation is non-linear, initially reducing losses but increasing them beyond a certain threshold. However, the study is limited by its focus on system-level cost implications without explicitly linking electricity losses to macroeconomic outcomes such as economic growth or sectoral productivity and its developed-country context restricts applicability to economies with higher structural inefficiencies. This study addresses these gaps by examining the impact of energy losses on sectoral economic growth in Kenya using a Cobb-Douglas production framework and the ARDL–ECM approach, thereby capturing both short-run and long-run dynamics and providing context-specific evidence from a developing economy where energy inefficiencies are more pronounced.

Adabor et al. (2022) examined the relationship between electricity transmission and distribution losses and economic growth in Ghana, responding to the limited empirical evidence on whether inefficiencies in electricity supply infrastructure constrain economic performance in developing economies. Using annual time series data for Ghana covering 1971–2014 and employing the ARDL model to estimate the short and long run effects of electricity losses on real gross domestic product and the Toda–Yamamoto approach to establish the direction of causality. The ARDL results showed that electricity transmission and distribution losses exerted a statistically significant negative effect on economic growth in both the short and long run, with the long-run coefficient ranging from −0.248 to −0.839 across alternative model specifications. The study attributed this adverse effect to the wastage of electricity that could otherwise support productive activities, reduced electricity availability, lower labour

productivity, higher production costs and constrained investment in electricity infrastructure. On the other hand, the Toda–Yamamoto results indicated unidirectional causality running from economic growth to electricity transmission and distribution losses, suggesting that expanding economic activity increases electricity demand and places additional pressure on transmission and distribution infrastructure, thereby generating greater losses. Although the study provides important evidence that electricity losses have economy-wide implications, it focused on aggregate GDP and therefore does not reveal how transmission and distribution losses affect individual productive sectors whose dependence on electricity, production structures and adjustment mechanisms may differ. The analysis also considered electricity losses as a general electricity infrastructure inefficiency rather than examining its implications within the context of Kenya's renewable energy transition. This leaves an important empirical gap regarding whether losses in the transmission-distribution of increasingly renewable generated electricity constrain sector-specific productive performance. This study addresses this gap by examining renewable energy transmission-distribution losses and their effects on manufacturing, services and agriculture in Kenya, thereby moving beyond the aggregate growth perspective to identify sector-specific consequences within a renewable energy transition framework.

Abeberese *et al.* (2021) investigated the impact of electricity supply disruptions on firm productivity in Ghana, emphasizing the economic consequences of electricity losses for growth. Using a survey of 885 small and medium-sized manufacturing firms across major industrial clusters in Ghana for the period 2011–2015, the study leverages quasi-random variation in electricity losses induced by a government rationing program to estimate productivity effects. The findings indicate that electricity losses significantly reduce labour productivity and total factor productivity, suggesting that eliminating these losses could increase productivity by approximately 10%, highlighting a strong connection between electricity consumption and economic output. Firms attempt to mitigate the impact of electricity losses through strategies such as using generators, adjusting production schedules and switching to less electricity-intensive processes; however, none of these approaches fully offset the negative effects and generator use may even aggravate productivity losses by diverting capital from core production activities. This study contributes to the literature by quantifying the economic costs of electricity inefficiencies at the firm level and examining the effectiveness of coping strategies, addressing gaps in prior research that primarily focused on large firms or overlooked small and medium enterprises, which account for the majority of employment and output in developing economies. The results highlight the importance of

policies aimed at reducing electricity losses to enhance firm productivity and support broader economic growth and they motivate further investigation into cost-effective interventions for firms operating under inefficient electricity supply. The study has documented the negative impact of electricity outages on firm productivity, but there is limited evidence on how overall electricity losses at the system level influence broader economic and sectoral growth, a gap this study addresses by empirically examining the effect of electricity losses on sectoral and national economic growth in Kenya.

The study by Osei-Gyebi and Dramani (2024) uses time series data from Ghana for the period 1980–2021 to examine electricity consumption, transmission losses and economic growth, employing an ARDL framework with a nonlinear specification. The findings show that transmission losses exert a strong long-run negative effect on electricity consumption and jointly reduce economic growth, highlighting how inefficiencies weaken the electricity–growth relationship. However, the study focuses only on national-level aggregates and does not assess sector-specific impacts or capture short-run versus long-run dynamics within production. This study addresses these gaps by analyzing the effect of energy losses on sectoral economic growth in Kenya using a Cobb-Douglas framework and an ARDL–ECM approach, providing both short-run and long-run, sector-specific evidence.

Nonthapot *et al.* (2025) investigated the influence of electricity consumption and economic growth on electricity losses within the transmission and distribution systems of Association of Southeast Asian Nations countries, covering the period 1990 to 2022. Using a Panel ARDL approach, the study finds that electricity consumption consistently contributes to higher energy losses in both continental and island ASEAN nations. On the other hand, economic growth is shown to reduce electricity losses overall, particularly in island countries, highlighting the role of increased economic resources in supporting investments in energy distribution infrastructure. The study further emphasizes that continental countries require ongoing development of their electricity distribution systems, while island nations may rely on economic stimulation policies to finance improvements that mitigate losses. However, the study does not examine the sectoral effects of electricity losses on economic growth, leaving a gap in understanding how losses in transmission and distribution directly impact different sectors of the economy. This study addresses this gap by analyzing the relationship between electricity losses and sectoral economic growth, providing detailed insights into how

inefficiencies in electricity distribution affect manufacturing, services and agriculture in a country-specific context.

Arthur et al. (2024) examined the relationship between electricity production, transmission and distribution losses in Ghana, with particular emphasis on the role of regulatory quality and institutional strength. Using annual time-series data for 1983–2018, the study first employed the Phillips Perron and Augmented Dickey Fuller tests to examine the stationarity properties of the variables and confirmed the existence of cointegration. The study subsequently applied the ARDL, estimating both a baseline specification and an extended model incorporating institutional quality and its interaction with electricity production. The findings indicate that stronger regulatory quality and institutional capacity significantly reduce electricity losses, highlighting the importance of effective institutions in improving the efficiency and reliability of electricity systems. The study also found that economic growth and electricity production were negatively associated with electricity losses, whereas labour force had a positive effect, while foreign direct investment and gross fixed capital formation were statistically insignificant. Although the study provides important evidence on the institutional and economic determinants of electricity losses, its focus on Ghana and the electricity sector leaves limited evidence on how transmission and distribution losses affect the performance of specific productive sectors. This gap is particularly relevant for economies such as Kenya, where improvements in renewable energy infrastructure and the reduction of energy losses may have differentiated implications for manufacturing, agriculture and services.

The study by Samuel (2023) uses data from Nigeria for the period 1981–2020 to examine how electricity losses in transmission and distribution affect GDP, employing a Vector Autoregressive model. The findings show that electricity losses negatively impact GDP, while electricity demand positively influences GDP and electricity supply has a negative effect. However, no causal relationship was found between losses, demand, supply and GDP. The study is limited by its focus on aggregate GDP rather than sectoral growth and does not capture short-run versus long-run dynamics. This study addresses these gaps by analyzing the effect of energy losses on sectoral economic growth in Kenya using a Cobb-Douglas production framework and ARDL–ECM methodology, providing both short-run and long-run, sector-specific evidence.

Edward (2023) investigates the impact of rural and urban electricity access on Ghana's economic growth while considering electricity transmission losses as a factor that may affect

growth outcomes. Using data from 1993 to 2018 and employing the Stock-Watson Dynamic Ordinary Least Squares methodology, the study finds differentiated effects of electricity access on economic performance. In particular, a 1% increase in overall electricity access is associated with a 0.073% decrease in economic growth, suggesting that mere growth of electricity access without addressing system inefficiencies may not translate directly into growth. However, the study highlights that increased rural electricity access positively affects national income per capita, with a 1% increase yielding a 0.527% rise, whereas urban electricity access shows no statistically significant effect. By incorporating electricity transmission losses into the analysis, the study demonstrates that minimizing power wastage is essential for electricity to contribute meaningfully to economic development. This study emphasizes the importance of improving electricity infrastructure and reducing technical losses to maximize the growth benefits of energy access. The gap that remains and which this study addresses is the broader, country-level assessment of how electricity losses across the transmission-distribution network influence sectoral economic growth, rather than focusing solely on rural versus urban access.

Das and McFarlane (2019) investigated the relationship between electric power losses, electricity consumption and economic growth in Jamaica using annual data for 1971–2014. Employing a nonlinear autoregressive framework, the study established a long-run relationship among the variables and found that positive shocks to electric power losses had a persistent negative effect on GDP. The findings suggest that increases in electricity losses can weaken the contribution of electricity infrastructure to economic activity by reducing the amount of electricity effectively available for productive use. This evidence is relevant to this study because it demonstrates that electricity losses are not merely an operational concern within the power sector but can have broader implications for economic performance. However, unlike Das and McFarlane (2019), this study focuses specifically on renewable energy transmission-distribution losses and their implications for productive-sector output in Kenya and how this problem is not merely a technical problem that needs fixing but also a significant economic problem.

Adamu *et al.* (2022) examined the economic consequences of electricity transmission and distribution losses in Nigeria, focusing on the performance of Electricity Distribution Companies. Using secondary data from the Nigerian Electricity Regulatory Commission and the International Centre for Investigative Reporting, the study finds that transmission and distribution losses are extremely high, averaging 53.83%, equivalent to about 1,973.318 MW

of electricity. This inefficiency translates into substantial economic losses, particularly for industrial consumers, with the highest recorded loss in YolaDisCo amounting to over fifty billion Naira in 2020. The study identifies overloading on transformers, vandalization of transmission equipment and poor maintenance regimes as key drivers of these losses. By quantifying the economic impact of electricity losses, the study emphasizes the critical role of efficient energy distribution in supporting economic growth. However, while the study effectively captures the aggregate economic cost of losses, it does not empirically investigate how these losses directly influence broader macroeconomic indicators such as national GDP growth or sectoral productivity. This presents a research gap that this study sought to fill, like the present one, that explicitly links electricity transmission-distribution losses to economic growth outcomes, thereby providing a more direct assessment of the impact of energy inefficiency on national economic performance.

Literature on the linkage that exists between power losses and development is from economies with different growth trajectories and dynamics compared to Kenya. The countries' socio-political and geographical contexts and alignments are different from Kenya and hence cannot be replicated. This study mitigated these shortcomings by focusing on data that is specific to the Kenyan context for ease of adoption.

2.4 Summary of Literature

Research gaps may arise from methodological, empirical, theoretical, population-based, evidence-based, knowledge and practical-knowledge limitations. The review of literature on renewable energy value chain dynamics and sectoral performance reveals gaps across several of these dimensions. Although existing studies have generated important evidence on the relationship between renewable energy value chain dynamics and sectoral growth and productivity, the literature remains fragmented in terms of methodological approaches, geographical coverage, measurement of renewable energy, sectoral coverage and treatment of dynamic relationships. An effective literature review should identify areas where existing knowledge is insufficient and provide a basis for advancing research in those areas (Webster & Watson, 2002). This study therefore builds on the existing evidence while addressing identified limitations within the context of Kenya.

Some methodological gaps are evident from the different analytical approaches employed in the reviewed studies. Identification of methodological gaps is important because it contributes to the development of appropriate and robust research designs (Creswell & Creswell, 2017).

Some studies relied on static specifications or analytical approaches that provide evidence of association but may provide limited information on how relationships evolve over time. This is particularly relevant to renewable energy because investments in generation capacity, technological adoption, electricity generation and energy use may not immediately translate into changes in productive-sector output. This study addresses this methodological concern by employing the ARDL framework, which allows for the examination of both short-run and long-run relationships among the variables. The framework also permits the effects of explanatory variables to be assessed at different lags, thereby providing a more appropriate representation of the dynamic relationship between renewable energy development and sectoral growth.

Another methodological gap concerns the treatment of dynamism in the renewable energy–growth relationship. The economic effects of changes in energy infrastructure and investment may emerge gradually because adjustment in production, technology and capital requires time. Thus, a contemporaneous relationship may not fully capture the effect of renewable energy development on economic performance. This study incorporates dynamic relationships through the ARDL framework, allowing both current and lagged effects of renewable energy variables to be estimated. This provides an opportunity to determine whether renewable energy installation, generation, consumption and transmission-distribution losses have immediate effects or whether their effects emerge over subsequent periods. The dynamic specification is therefore particularly relevant to the annual time-series nature of the Kenyan data used in this study.

Empirical gaps also arise from the limited availability of evidence for particular contexts and relationships. Such gaps provide a basis for further research that extends and contributes to existing knowledge (Webster & Watson, 2002). The reviewed studies were conducted across different countries and economic settings, including developed, emerging and developing economies. Differences in economic structures, energy systems, institutional arrangements, resource endowments and development trajectories mean that findings from one country cannot automatically be generalized to another. This is particularly important for Kenya, whose renewable-energy system and productive structure have characteristics that may produce different outcomes from those observed elsewhere. This study therefore contributes additional country-specific evidence by examining the renewable energy–sectoral growth relationship within the Kenyan economy.

Existing literature also presents mixed empirical evidence concerning the relationship between renewable energy value chain dynamics and sectoral performance. While some studies report positive growth effects associated with renewable energy development, others find weak, insignificant or context-dependent relationships. Such differences may partly reflect variations in countries, study periods, estimation techniques and the measurement of renewable energy. Renewable energy installation, generation and consumption represent different stages of the energy system and may therefore have different implications for economic activity. Therefore, treating renewable energy as a single homogeneous construct may obscure important differences in its economic effects. This study seeks to reduce this ambiguity by separately examining renewable energy installation, generation and consumption and by additionally incorporating transmission-distribution losses into the analysis.

Population-based gaps are also evident because the findings of studies conducted in other economies may not necessarily be replicated in Kenya. Even countries within the same broad category of developing economies can have substantially different energy resource endowments, electricity-generation structures, institutional environments and economic activities. For instance, African economies such as Nigeria may have different energy dynamics from Kenya despite sharing similarities in their development status. These differences can influence the effectiveness of renewable energy investments and the extent to which renewable energy contributes to productive activity. By focusing specifically on Kenya, this study provides evidence from a population and economic setting that is directly relevant to the country's energy and sectoral development policies and provides a basis for comparison with economies exhibiting similar development and energy characteristics.

Another gap concerns the specification of the determinants of economic performance. Economic and sectoral growth is influenced by several factors beyond energy, including capital accumulation, labour, investment, technological progress and other macroeconomic conditions. Thus, models that focus narrowly on energy may provide an incomplete representation of the determinants of economic performance. This study addresses this concern by incorporating relevant control variables alongside the renewable-energy variables. This enables the estimated effects of renewable energy to be examined while accounting for other observable factors that may influence sectoral growth, with unobserved influences accommodated through the stochastic error term. The study is theoretically anchored in the neoclassical Solow-Swan growth model, which provides a framework for understanding the contribution of productive inputs and technological progress to output. The model is linearized

to facilitate empirical estimation of the relationships between renewable energy development and sectoral economic performance.

Evidence-based gaps concern the economic implications of transmission and distribution losses within the renewable-energy system. Evidence-based gaps arise where available evidence is insufficient to establish whether an existing proposition or practice is supported. Although electricity losses are an established concern within electricity systems, their specific implications for productive-sector performance require empirical assessment. Energy generated from renewable sources does not necessarily translate into an equivalent quantity of electricity available to productive users because part of the electricity may be lost during transmission and distribution. Such losses could potentially constrain production by reducing the quantity and reliability of electricity reaching firms and other economic users. However, the magnitude and direction of this relationship should be established empirically rather than assumed. This study therefore contributes evidence by explicitly incorporating transmission-distribution losses and examining their relationship with manufacturing, services and agricultural growth in Kenya.

The literature also reveals a practical-knowledge gap concerning the extent to which renewable energy development translates into productive economic activity. Existing evidence provides important information about renewable-energy expansion and economic growth, but the economic benefits of energy development ultimately depend on the extent to which energy is effectively generated, delivered and utilized. High levels of installed renewable capacity may not produce corresponding economic benefits if generation is inadequate, consumption is constrained or substantial electricity is lost within the transmission and distribution system. This study addresses this practical dimension by examining different stages of the renewable energy chain rather than considering renewable energy solely as an aggregate concept. This approach provides evidence that can inform policy decisions concerning not only renewable-energy expansion but also electricity generation, utilization and delivery efficiency.

Another important knowledge gap concerns the level at which economic and sectoral performance is measured. A substantial proportion of the literature examines economic growth using aggregate GDP, which may conceal differences in the effects of renewable energy across productive sectors. Similarly, studies that use aggregate energy measures may not adequately isolate the economic contribution of renewable energy from that of other energy sources. This study addresses these limitations by focusing specifically on renewable-energy variables and

disaggregating economic performance into manufacturing, services and agriculture. This sectoral approach is important because the sectors differ in their production structures, energy requirements and dependence on reliable electricity supply. Thus, renewable energy may produce heterogeneous effects across sectors that cannot be adequately captured using aggregate GDP.

Time lags represent another important consideration in understanding the renewable energy–sectoral growth nexus. Economic decisions and investments generally require time before their effects are reflected in production because of technological, institutional and adjustment processes. Renewable-energy investments, for example, may initially involve substantial capital expenditure before generating sufficient electricity to influence productive activity. Similarly, changes in electricity generation or consumption may take time to affect sectoral output. This study addresses this issue through the distributed-lag structure of the ARDL model, which allows the effects of renewable-energy variables to emerge over successive periods. Since the study employs annual data, the lag structure is expressed in annual periods and provides an opportunity to capture delayed responses that may otherwise be overlooked in a purely contemporaneous model.

A temporal gap also exists in the renewable energy–sectoral productivity literature. Temporal gaps can arise where evidence is insufficient for particular periods, resulting in discontinuities in knowledge about how relationships evolve over time (Booth et al., 2022). The renewable-energy sector has undergone substantial changes in recent years as countries have expanded renewable-energy capacity, adopted new technologies and implemented policies aimed at increasing renewable-energy penetration. Evidence based on older periods may therefore not fully capture the current structure and dynamics of the energy sector. This study addresses this gap by exploiting a relatively recent and sufficiently long annual dataset for Kenya, thereby providing evidence that reflects the contemporary relationship between renewable-energy development and productive-sector performance. The findings are expected to provide policy-relevant evidence for Kenya and potentially offer lessons for economies with comparable development levels and renewable-energy resource endowments.

There is also a spatial gap in the literature. Spatial gaps arise where particular geographical locations or regions remain insufficiently studied, limiting the extent to which existing findings can be generalized across contexts. Studies in the energy–sectoral growth nexus have not covered all countries and regions with comparable economic and energy characteristics,

creating a need for context-specific evidence (Cope & Elwood, 2020). Even where countries have similar levels of economic development or renewable-energy resource endowments, differences in political, institutional and social environments can influence energy policies, investment decisions and economic outcomes. Kenya therefore provides an important setting for extending the literature because its renewable-energy resource base, electricity system and sectoral economic structure create a distinctive context in which the renewable energy–sectoral growth relationship can be examined.

The reviewed literature demonstrates that renewable energy can influence economic and sectoral performance, but important gaps remain concerning the measurement of renewable energy, sectoral heterogeneity, dynamic effects, transmission and distribution losses, geographical applicability and the recency of empirical evidence. Existing studies have generated valuable findings; however, they predominantly examine individual renewable energy value chain dynamics and often use aggregate economic growth as the outcome variable. Their differences in contexts, measures and methodologies therefore make it difficult to establish how the interconnected dimensions of renewable energy development jointly and individually influence productive-sector performance. This fragmentation also explains why the empirical literature in this study is organized by renewable energy value chain dynamics rather than by sector: reviewing the literature by installation, generation, consumption and transmission and distribution losses makes it possible to synthesize the evidence surrounding each component of the value chain while retaining the substantial body of aggregate-growth literature, which would otherwise be fragmented or excluded under a strictly sector-based organization. In particular, the review identified no empirical study that evaluates these four value chain dynamics jointly as a composite renewable energy value chain framework and relates them separately to manufacturing, services and agricultural growth. This study addresses this gap through an integrated framework that examines renewable energy installation, generation, consumption and transmission and distribution losses and assesses their respective influences on manufacturing, services and agricultural growth in Kenya. The joint modelling of these value chain dynamics is important because they represent interconnected dimensions of the renewable energy value chain; estimating them within a common framework allows the influence of each dynamic to be assessed while accounting for the presence of the others, thereby providing a more comprehensive understanding of their sectoral effects. Methodologically, the ARDL framework further enables the study to distinguish between short-run and long-run relationships and account for lagged effects. The

study therefore contributes methodological, empirical, geographical, temporal and practical knowledge to the renewable energy–sectoral growth literature while generating policy-relevant evidence on how renewable energy development and the efficiency of electricity delivery translate into productive-sector performance in Kenya.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

This chapter details the study's philosophy, research design, study area, study area, data types, model adopted, data set and measurement of the variables, data sources, analysis, as well as presentation of research outputs.

3.2 Philosophy of the Study

This study adopted a pragmatist research philosophy to engage directly with real-world dynamics of renewable energy and sectoral growth. Pragmatism is particularly suitable for this study due to its methodological flexibility, practicality and capacity to address multiple dimensions of the research problem (Johnson & Onwuegbuzie, 2004). It allowed the study to select and integrate methods based on the research objectives, the nature of the research problem as well as the characteristics of the data to examine how renewable energy installation, generation, consumption and transmission-distribution losses influence the performance of the manufacturing, services and agriculture sectors in Kenya. By emphasizing what works in practice, pragmatism facilitates the generation of policy-relevant insights without being restricted by rigid methodological constraints. Thus, it aligns seamlessly with the study's objective of understanding the influence of renewable energy value chain dynamics on sectoral growth, integrating both empirical analysis and theoretical reasoning.

3.3 Research Design

According to Creswell and Creswell (2017), a research design is a plan and procedure for an intended research work. It further asserts that the choice of a research design relies significantly on study objectives, the characteristics of the research problem and the nature of the data being considered. This study adopted a plan that focuses on maintaining clear research actions and goals, as suggested by Cohen *et al.* (2002). According to Kothari (2004), a correlational research design is suitable for examining relationships among multiple variables. Accordingly, this study employed this design to investigate the influence of green energy dynamics on sectoral growth in Kenya. This study, therefore, embraced a correlational framework because it relied upon secondary macroeconomic time-series data that could not be experimentally manipulated. This design is appropriate for examining the degree and direction of association between renewable energy indicators and sectoral outputs over time. While correlational

designs do not establish definitive causality and may be influenced by unobserved factors, they provide a clear framework for identifying patterns, trends and relationships amongst variables. It also offers meaningful insights into how changes in renewable energy are linked to sectoral growth.

Yearly historical datasets sourced from EIA and the WDI spanning the 1980-2024 period were utilized to unearth the influence of the selected green energy dynamics and how they influenced the growth of Kenya's productive sectors. This extensive dataset enabled the study to understand the interrelationships that exist among the variables and their implications to help in forecasting and policymaking.

This choice of a correlational research design is therefore anchored in the pragmatist research philosophy adopted in this study, which emphasizes the selection of methods based on their suitability in addressing the research problem rather than adherence to a single methodological tradition. Pragmatism allows the researcher the flexibility to choose approaches that best provide practical and reliable answers, particularly where the nature of the data and research objectives are clearly defined (Creswell & Creswell, 2017; Saunders et al., 2011; Mackenzie & Knipe, 2006). In this case, the reliance on quantitative time-series data and the objective of examining relationships between renewable energy value chain dynamics and sectoral growth necessitated a design capable of capturing measurable associations among variables. Therefore, the correlational design is considered most appropriate, as it aligns with the pragmatist emphasis on real-world applicability and evidence-based analysis while enabling the generation of robust and policy-relevant findings.

3.4 Study Area

This research majorly focused on Kenya's energy and economic sectors. Located in Eastern Africa, Kenya is bordered by Ethiopia, Tanzania, Uganda, Somalia and South Sudan. It is positioned at a latitude of 0.4252°S and a longitude of 36.7517°E. As per the 2019 census, Kenya's population is approximately 47 million (KNBS, 2019).

Kenya's sectoral growth is driven by the agricultural, manufacturing and services sectors. The agricultural sector in Kenya contributes about 33% of its GDP. The sector also provides employment opportunities for approximately 60% of the total Kenyan labour force. It is characterized by small-scale farming, producing key export goods like tea, coffee and horticultural products. However, agricultural growth remains low due to climate variability, with only 20% of arable land being under cultivation. The manufacturing sector contributes

approximately 8.3% to the GDP, focusing on agro-processing, textile production and construction materials. Despite its potential, growth in this sector has been slow, partly due to high energy costs and inefficiencies in supply chains. The services sector, accounting for about 43% of GDP, has been the fastest-growing, driven by ICT, tourism and financial services. Kenya is now a regional leader in mobile banking through M-Pesa and the ICT sector contributes approximately 8% to GDP. Efforts to boost growth in all these sectors include renewable energy integration, improved infrastructure and policies outlined in Vision 2030 to foster industrialization and modernization (KNBS, 2023).

In terms of renewable energy endowments, Our World data (2024) reports that Kenya is acknowledged as a frontrunner in renewable energy capacity in Africa, having about 90% of its total power emanating from renewable energy sources. As of the year 2022, Kenya's installed renewable energy generation potential reached around 2,453 MW, with about 70% being derived from renewable sources. Kenya is the seventh-largest producer of geothermal energy globally, with the Olkaria geothermal power station contributing over 700 MW to the national grid. Hydropower, mainly from the Tana River Basin, accounts for approximately 30% of the total electricity generation, while wind energy, particularly from the Lake Turkana Wind Power project, contributes about 17% to the energy mix. Despite this progress, the energy access rate in Kenya stands at about 75%, with notable differences being recorded between the urban and rural regions. The state has established bold but achievable goals aimed at green energy within the total energy portfolio in order to ultimately attain universal electricity access by 2025 through policies outlined in the Least Cost Power Development Plan of 2017 and also in the National Energy and Petroleum Policy of 2018.

3.5 Econometric Model

This body of knowledge exploited the Cobb-Douglas production framework in a bid to examine the influence of the selected renewable constructs on the growth of Kenya's manufacturing, service and agricultural sectors. The study employed a Cobb-Douglas production function derived from the Solow-Swan growth model because it provides a theoretically grounded framework for examining sectoral output. Its functional form allows the estimation of elasticities, enabling the effects of renewable energy, labour and capital on sectoral growth to be interpreted directly as percentage changes, thereby offering clear and policy-relevant insights into how changes in inputs translate into changes in output. Renewable energy variables were treated as proxies for Total Factor Productivity rather than separate inputs because they improve the efficiency of labour and capital, representing technological progress

and energy efficiency. This approach captures how renewable energy contributes to long-term sectoral growth without creating overlap and redundancy with traditional inputs. This aligns with both economic theory and previous research. (Solow, 1956).

It is assumed that the renewables have a significant contribution as far as determining the output levels of agricultural, service and manufacturing sectors in Kenya is concerned. However, this relationship could also be impacted by various extraneous elements such as capital, labour and the selected non-renewable energy dynamics. This is because the variables can't interact with each other uninterrupted. As highlighted by Gujarati and Porter (2009), the Cobb-Douglas framework is a critical tool in determining, assessing and estimating relationships involving nonlinear variables with varying and fluctuating slopes. As per the basic equation 1.1 , ultimately, the model was linearized by the introduction of logs.

In the Solow-Swan model-based Cobb-Douglas production framework, production is expressed as a function of capital and labour, with total factor productivity, denoted as *A*, representing the efficiency with which these inputs are combined for a given level of output. However, in the context of Kenya's sectoral growth, energy dynamics are instrumental in the determination of sectoral growth. Therefore, this study extends the conventional production function by incorporating renewable energy variables: installation, generation, consumption and losses as observable proxies for total factor productivity. These variables capture the technological and efficiency effects that *A* represents, given that energy availability and utilization influence the capacity of firms and households to translate capital and labour into productive output. By introducing energy variables as part of the productivity component, the model accounts for the fact that differences in sectoral performance are not solely attributable to capital accumulation and labour input, but also to the efficiency with which energy resources are deployed. This specification not only aligns with theoretical extensions of the Cobb–Douglas framework that incorporate energy as a productivity-enhancing factor but also reflects empirical evidence from both developed and developing economies, which demonstrates that energy systems are critical determinants of growth (Al-Ayouty, 2020; Eggoh *et al.,* 2011; Gava *et al.,* 2025). Therefore, the renewable energy constructs: installation, generation, consumption and losses were treated as drivers and inputs while labour and capital were integrated as control variables.

For purposes of this investigation, sectoral output variables for agriculture, services and manufacturing were used in their absolute values rather than percentages. This choice aligns

with standard time series econometric practice, where the actual magnitude of economic activity is preferred to maintain interpretability in real-world terms. Going with the suggestions of Kothari (2004), Sectoral output was measured in absolute values and then log-transformed to stabilize variance, reduce heteroscedasticity and linearize exponential growth trends commonly found in macroeconomic time-series data. This transformation also allows for elasticity-style interpretation**,** where estimated coefficients indicate the change expressed as a percentage in output resulting from a change expressed as a percentage in explanatory variables. Using real growth rates could have distorted some computations because certain growth rates were negative for some periods, which would have posed problems during log transformation. While log transformation provides these advantages, it assumes that all values are positive and may not reveal short-term fluctuations in the data.

The absolute values were also log-transformed to address issues of scale and potential non-stationarity and also stabilize the variance, which is beneficial for both descriptive and inferential analysis. This approach is consistent with the propositions made by Wooldridge (2016), Gujarati and Porter (2009), Enders (2008) and Mankiw *et al.* (1992) who advocate for using transformed data, such as logs, throughout the analysis when such transformations are applied.

The linearized Cobb-Douglas function expressing the influence and implications of installing renewables on the performance of the agricultural, service and manufacturing subsectors was represented by equation by the basic equation 1.2.

$$Y_t = A_t RE_t K_t^{\alpha} L_t^{1-\alpha} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . \ldots \ldots \ldots \ldots \ldots \ldots .. (1.2)$$

The output in this case is defined by two crucial inputs, capital and labour. The exponents represent the contribution and output elasticities of each of the sectors while holding technology constant.

Now, recognizing that power is a critical contributor to the process of production, the function can be expanded to include renewable energy value chain dynamics. This yields equation 3.1;

$$Y_{jt} = ARET_t^{\alpha_1} REG_t^{\alpha_2} REC_t^{\alpha_3} RNTL_t^{\alpha_4} GCF_t^{\alpha_5} L_t^{\alpha_6}\ \varepsilon_t\ \ldots \ldots \ldots \ldots \ldots \ldots \ldots . \ldots \ldots \ldots . \ldots \ldots \ldots \ldots \ldots (3.1)$$

Where Y_{jt} represents the productive sectors' performance at time t;

j is the individual productive sector; that is, manufacturing, service and agriculture at time t;

RET_t is the renewable energy installed capacity in period *t;*

REG_t represents renewable energy generation during time *t;*

REC_t is renewable energy consumption, during time t;

$RNTL_t$ is the renewable energy transmission-distribution losses, during time t;

GCF_t represents gross capital formation in time *t;*

L_t represents labour at time *t* and

ε_t represents the error term in period *t*.

In this specification, renewable energy constructs are incorporated as productive inputs alongside capital, *GCF* and labour, *L,* which were incorporated as control variables. *A* is the level of technology, while ε_t is the error or stochastic term. This extension captures the empirical reality that energy infrastructure largely complements the traditional elements as far as the determination of economic performance is concerned, for this scenario, sectoral output and performance.

To achieve empirical estimation, the multiplicative form in equation 3.1 is linearized by the introduction of natural logs.

This study is anchored in an augmented Cobb–Douglas production framework derived from the Solow–Swan growth model, where aggregate output is determined by conventional inputs: capital and labour, alongside renewable energy value chain dynamics (Solow, 1956; Cobb & Douglas, 1928). In this extended structure, renewable energy installation, generation, consumption and transmission-distribution losses are incorporated as additional productive inputs, reflecting their dual role as both direct contributors to output and facilitators of technological progress. This extension is consistent with a growing body of literature that recognizes energy as a fundamental driver of economic performance and structural transformation (Stern, 2000, 2011; Apergis & Payne, 2010).

To adequately capture the nonlinear and potentially asymmetric relationship between energy variables and output, the model is specified in a semi-log functional form. This specification allows the dependent variable to respond proportionally to changes in selected regressors while retaining level effects for variables whose marginal contributions are not expected to exhibit constant elasticities. From an econometric standpoint, semi-log models are particularly useful in contexts where some explanatory variables exert diminishing or threshold-dependent effects on output, as is often the case with energy infrastructure and efficiency improvements

(Wooldridge, 2016). The semi-log structure therefore provides a flexible and theoretically consistent framework for modelling heterogeneous responses within the production process.

Furthermore, the empirical model is estimated using a dynamic ARDL framework, which incorporates both contemporaneous and lagged values of the regressors. This approach is appropriate given that adjustments in energy systems and capital accumulation occur gradually due to investment gestation periods, technological diffusion and institutional rigidities. By capturing both short-run dynamics and long-run equilibrium relationships, the ARDL specification aligns with the value chain dynamics implied by neoclassical growth theory while allowing for differential speeds of adjustment across sectors (Pesaran et al., 2001).

The general model specification takes the form for each sector takes the form;

$$Y_{jt} = \alpha_0 + \alpha_1 LnRET_t + \alpha_2 LnREG_t + \alpha_3 REC_t + \alpha_4 LnRNTL_t + \alpha_5 GCF_t + \alpha_6 L_t + \alpha_7 LnRET_{t-i} + \alpha_8 LnREG_{t-i} + \alpha_9 REC_{t-i} + \alpha_{10} LnRNTL_{t-i} + \alpha_{11} GCF_{t-i} + \alpha_{12} L_{t-i} + \varepsilon_t \quad (3.2)$$

Where;

$$Y_{jt} = \begin{pmatrix} MVA_t \\ SER_t \\ AVA_t \end{pmatrix} \quad (3.3)$$

For objective one, manufacturing value added;

$$MVA_t = \alpha_0 + \alpha_1 LnRET_t + \alpha_2 LnREG_t + \alpha_3 REC_t + \alpha_4 LnRNTL_t + \alpha_5 GCF_t + \alpha_6 L_t + \alpha_7 LnRET_{t-i} + \alpha_8 LnREG_{t-i} + \alpha_9 REC_{t-i} + \alpha_{10} LnRNTL_{t-i} + \alpha_{11} GCF_{t-i} + \alpha_{12} L_{t-i} + \varepsilon_t \quad (3.4)$$

For objective two, service;

$$SVA_t = \alpha_0 + \alpha_1 LnRET_t + \alpha_2 LnREG_t + \alpha_3 REC_t + \alpha_4 LnRNTL_t + \alpha_5 GCF_t + \alpha_6 L_t + \alpha_7 LnRET_{t-i} + \alpha_8 LnREG_{t-i} + \alpha_9 REC_{t-i} + \alpha_{10} LnRNTL_{t-i} + \alpha_{11} GCF_{t-i} + \alpha_{12} L_{t-i} + \varepsilon_t \quad (3.5)$$

For objective three, the value added;

$$AVA_t = \alpha_0 + \alpha_1 LnRET_t + \alpha_2 LnREG_t + \alpha_3 REC_t + \alpha_4 LnRNTL_t + \alpha_5 GCF_t + \alpha_6 L_t + \alpha_7 LnRET_{t-i} + \alpha_8 LnREG_{t-i} + \alpha_9 REC_{t-i} + \alpha_{10} LnRNTL_{t-i} + \alpha_{11} GCF_{t-i} + \alpha_{12} L_{t-i} + \varepsilon_t \quad (3.6)$$

The log-linearization ensures that the logged parameters can be interpreted as elasticities of output with respect to the respective inputs, thereby making the model both statistically tractable and economically meaningful. This form of the model was applied across the board in this study.

The study adopts a linear-log model in which selected explanatory variables are transformed into natural logarithms while others are retained in levels. Specifically, renewable energy installation, generation and losses are expressed in logarithmic form to stabilize variance, reduce the influence of extreme values and capture proportional changes in energy dynamics. This transformation also enables the coefficients of these variables to be interpreted as semi-elasticities, reflecting the percentage response of sectoral output to changes in energy-related variables.

On the other hand, renewable energy consumption, gross capital formation, labour and the dependent variables representing sectoral output are maintained in levels. This is because these variables are measured in meaningful absolute units and their direct inclusion preserves their economic interpretation in terms of marginal contributions to output. Also, retaining these variables in levels avoids potential distortions that may arise from logarithmic transformation, particularly where values may exhibit limited variability or contain zero observations.

The log–level specification provides a flexible framework that captures both proportional effects of renewable energy value chain dynamics and absolute effects of traditional performance factors, making it suitable for analyzing sectoral growth within the ARDL framework.

To include temporal dynamics, lags were incorporated in the models, as the impacts of energy policies and decisions do not occur instantaneously (Granger, 1969). A conventional lag structure of one period was initially adopted to specify the ARDL models, providing a starting framework for capturing both short-run dynamics and potential delayed effects of renewable energy on sectoral performance. The lags also helped account for delayed responses in sectoral outputs, reflecting the time required for adjustments in production processes and energy utilization. The coefficients are not logged because they represent elasticities or proportional changes. The inclusion of both lagged and non-lagged variables allows the models to test for persistence or delayed responses in the relationships, while the exact lag length for each variable was subsequently determined empirically during the ARDL estimation using the AIC criterion. This combination of a conventional starting point and data-driven lag selection

ensures both methodological rigor and empirical accuracy in estimating the short-run and long-run effects of renewable energy dynamics on sectoral outputs.

Linearizing the Cobb-Douglas function serves to simplify estimation, enhance interpretability, align with growth rate analysis, address econometric issues and help maintain theoretical consistency, making it ideal for empirical economic research (Heathfield, 1971).

3.6 Data Sources and Measurement of Variables

This study's dataset covered the period 1980-2024; this timeframe preceded the global energy crisis triggered by the 1970s oil embargo imposed by Arab oil-exporting nations. It therefore made use of a 43-year dataset. The main variables are manufacturing output, service output, agricultural output, renewable energy installations, renewable energy generation, renewable energy net transmission-distribution losses and renewable energy consumption, while capital and labour were adopted as the controls. This research utilized annual time series secondary data obtained from the WDI and the EIA. Secondary data refers to information previously gathered (Kombo & Tromp, 2006), typically involving the utilization of publicly available datasets.

Table 3.1 provides a summary of the data sources and how they will be measured.

Table 3.1. ***Data Sources and Types***

Variables	Description	Measures	Sources	Objective Being Addressed	Prior Expected sign
Agriculture(AVA).	-Agriculture, forestry and fishing, value added (current LCU)(Indicator code-NV.AGR.TOTL.CN, WDI)	-Ksh(billions)	-WDI	1,2 and 3	+/-
Service (SVA)	-Services, value added (constant LCU)(Indicator code-NV.SRV.TOTL.KN, WDI)	-Ksh(billions)	-WDI	1,2 and 3	+/-
Manufacturing(MVA)	Manufacturing, value added (current LCU)(Indicator code-NV.IND.MANF.CN, WDI)	-Ksh(billions)	-WDI	1,2 and 3	+/-

Renewable Energy Consumption(REC)	-Total energy consumption from renewables and other, Kenya, Annual	-KWh	-EIA	1,2 and 3	+/-
Renewable Energy Installation(RET)	-Renewable electricity installed capacity, Kenya, Annual	-KW	-EIA	1,2 and 3	+/-
Renewable Energy Generation(REG)	-Renewable electricity net generation, Kenya, Annual	-KWh	-EIA	1,2 and 3	+/-
Renewable Energy transmission-distribution losses(RNTL)	-Renewable Energy Generations(REG) less Renewable Energy Consumption(REC)	-KWh	- EIA	1,2 and 3	+/-
Gross Capital Formation(GCF)	-Gross fixed capital formation(GCF) (constant LCU), indicator code-NE.GDI.FTOT.KN, WDI	- Ksh(billions)	- WDI	1,2 and 3	+/-
Labour(L)	-Labour force, total(indicator ID-SL.TLF.TOTL.IN)	-M(millions)	- WDI	1,2 and 3	+/-

(Source: Author, 2026)

This study followed established data security protocols as outlined in sources such as Babbie (2020), the Data Protection Act (2019) and the International Data Sharing Guidelines (2020) to ensure proper storage, protection and handling of secondary data. Since this study utilized secondary data from publicly available sources such as the WDI and the EIA, the data storage and protection requirements differed from those of primary data collection. These sources follow rigorous data security protocols to ensure that the data is secure and protected from unauthorized access. These measures include encryption during data transmission, secure servers for storage and adherence to data protection regulations to safeguard the data's integrity and confidentiality.

For this study, the secondary data obtained from these reputable, verified and authorized databases was downloaded and stored in password-protected files on the researcher's personal, secure computer system. Additionally, the files were backed up to an encrypted cloud storage

service. Access to these files was restricted to the researcher and relevant academic advisors, ensuring controlled access and security. The use of encrypted storage guaranteed that the data remained secure throughout the study's duration.

This research ensured that all data was used in accordance with the terms of use established by the respective databases: the WDI as well as the EIA. As this study did not involve personal or confidential data, the primary focus was on maintaining the integrity, accuracy and appropriate use of the secondary data. Proper citation and referencing were rigorously adhered to acknowledge the data sources accurately and in compliance with academic standards.

Since the data used in this study is secondary and publicly available, there were no specific sensitive data concerns to address. However, any necessary archival or deletion of data was performed in accordance with the institution's guidelines.

3.6 Tests for Validity and Reliability

3.6.1 Tests for Validity

Validity refers to the extent to which a research instrument, measure, or data collection process accurately represents the concept or phenomenon that it is intended to measure (Creswell & Creswell, 2017). Although this study relied on secondary rather than primary data, the principle of validity remained important because the credibility of the empirical findings depended on whether the selected secondary indicators appropriately represented renewable energy value chain dynamics and sectoral economic performance in Kenya. Validity in this study concerned the appropriateness, relevance and representativeness of the selected variables and data sources in capturing the relationships specified in the study objectives. This was particularly important because the study sought to provide empirical evidence relevant to energy policy and sustainable economic development in Kenya.

Content validity was addressed through the selection of secondary data that adequately covered the key dimensions of the concepts investigated. Data were obtained from reputable and established sources, particularly the WDI and the EIA, which provide extensive economic and energy-related datasets. The use of these sources enabled the study to capture the principal dimensions of renewable energy value chain dynamics, including renewable energy installation, generation, consumption and losses, alongside measures of sectoral economic performance. Thus, the variables selected were not based on isolated observations but on indicators that corresponded to the conceptual dimensions examined in the study. This

approach is consistent with the principle that content validity requires adequate coverage of the relevant dimensions of a concept under investigation (Babbie, 2020).

Construct validity was addressed through the use of indicators that had clear conceptual links to the theoretical constructs of renewable energy dynamics and sectoral performance. For renewable energy value chain dynamics, indicators such as renewable energy installed capacity, renewable energy generation, renewable energy consumption and renewable energy transmission-distribution losses were employed to represent the different stages and dimensions of the renewable energy system. Sectoral performance was represented using appropriate measures of economic output for the manufacturing, services and agricultural sectors. The use of established energy indicators is consistent with their longstanding application in the analysis of energy systems and energy-related economic processes (Yergin, 2011). Thus, the operationalization of the study variables provided a reasonable correspondence between the theoretical concepts and their empirical measures, thereby strengthening construct validity.

Criterion-related validity was considered by examining whether the selected indicators were consistent with established economic and energy performance measures. In particular, the sectoral performance indicators were considered alongside broader measures of economic performance, including GDP growth and sector-specific economic and productivity measures, where appropriate. This provided a basis for assessing whether the selected indicators behaved consistently with established measures of economic performance. Rather than implying that the secondary data independently predicted sectoral outcomes, criterion-related validity in this study was therefore concerned with the extent to which the operational measures corresponded to recognized economic performance indicators. Such consistency provided additional support for the appropriateness of the selected measures for empirical analysis.

External validity was considered in relation to the extent to which the findings could provide useful insights beyond the specific Kenyan context. The use of internationally recognized and systematically compiled secondary databases enhanced comparability between Kenya and other economies that may experience similar renewable energy transitions. However, because the study focused specifically on Kenya, generalization to other developing countries was made cautiously. The findings were primarily interpreted within the Kenyan institutional, economic and energy context, while their potential relevance to other developing economies was considered where those economies share comparable characteristics in terms of energy value

chain and economic structures. Thus, the use of standardized international data sources strengthened the potential transferability and comparability of the findings without implying that the results were automatically generalizable to all developing countries.

Internal validity was strengthened through the systematic specification and estimation of the time-series econometric models. The study employed unit-root tests, lag selection procedures, the ARDL bounds-testing approach and the associated error-correction framework to establish the temporal and long-run relationships among the variables. These procedures helped to reduce the risk of drawing misleading conclusions from non-stationary time-series relationships and enabled the study to distinguish between short-run dynamics and long-run relationships. In addition, the inclusion of relevant explanatory variables and appropriate lag structures helped account for the dynamic nature of the relationships under investigation. Internal validity was therefore approached through the careful specification, estimation and diagnostic evaluation of the econometric models rather than through an assumption that time-series analysis automatically eliminates all possible confounding influences. These procedures enhanced confidence that the estimated relationships between renewable energy value chain dynamics and sectoral performance were empirically grounded and appropriately derived from the secondary data.

3.6.2 Tests for Reliability

Reliability refers to the consistency and stability of a measurement process or the extent to which a measure produces consistent results under similar conditions (Creswell & Creswell, 2017). Although this study employed secondary rather than primary data, reliability remained important because the credibility of the empirical results depended on the consistency, accuracy and reproducibility of the data and analytical procedures. In this study, therefore, reliability was considered in terms of the consistency of the secondary data, the stability of the measurement indicators, the comparability of information obtained from different sources and the reproducibility of the analytical procedures used to examine the relationship between renewable energy value chain dynamics and sectoral development.

To enhance data reliability, secondary data were obtained from established and reputable sources, particularly the WDI and the EIA. Where comparable information was available from more than one source, the reported values, definitions, units of measurement and time coverage were examined for consistency. This process of cross-checking helped identify potential discrepancies and reduced the possibility that the empirical results would be unduly dependent

on errors or inconsistencies associated with a single data source. The use of established secondary databases also enhanced the transparency and reproducibility of the study because the datasets and their underlying definitions could be independently accessed and examined by other researchers (Babbie, 2020).

Source triangulation was further employed to strengthen the reliability of the data. Information obtained from the WDI and EIA was compared where the same or closely related indicators were available. Differences in definitions, measurement units, coverage or reporting periods were considered before the data were incorporated into the analysis. This was particularly important for energy-related variables because differences in measurement conventions across databases can affect comparability. Through such verification, the study sought to ensure that the final dataset used in the econometric analysis was internally consistent and suitable for the specified time-series models.

Measurement reliability was enhanced through the use of established and consistently defined indicators for the principal study constructs. Renewable energy value chain dynamics were measured using indicators such as renewable energy installed capacity, renewable energy generation, renewable energy consumption and renewable energy losses, while sectoral performance was measured using appropriate sector-specific economic output indicators. The use of indicators that have been widely employed in energy and economic analysis provides greater consistency in the operationalization of the study variables and facilitates comparison with previous empirical studies (Yergin, 2011). Maintaining consistent definitions and measurement units throughout the study period further reduced the likelihood that changes in the variables were attributable to changes in measurement rather than actual changes in the underlying phenomena.

Reproducibility of the research process was also considered an important dimension of reliability. The study clearly specified the data sources, variable definitions, transformations, sample period, model specifications, lag-selection procedure and econometric estimation techniques. The systematic application of these procedures means that another researcher using the same datasets, definitions and methodological specifications should be able to reproduce the analytical process and assess the consistency of the findings. This is particularly relevant to a secondary-data study because reliability depends not only on the quality of the original data but also on the transparency and consistency with which those data are processed and analyzed.

Analytical reliability was further enhanced through the application of appropriate time-series econometric procedures. The study employed unit-root tests, lag-selection criteria, ARDL bounds testing, error-correction modelling and relevant diagnostic tests to assess the properties and stability of the estimated relationships. These procedures helped establish whether the estimated relationships were statistically and econometrically consistent with the properties of the underlying data. The use of appropriate diagnostic and specification tests also reduced the likelihood that the reported findings were driven by model misspecification, serial correlation, heteroscedasticity, or other statistical problems.

Reliability in this study was established primarily through the use of reputable and traceable secondary data sources, cross-checking and triangulation of available information, consistent operationalization of variables, transparent data-processing procedures and reproducible econometric analysis. These measures provided a reliable empirical foundation for examining the relationship between renewable energy value chain dynamics and the performance of Kenya's economic sectors.

3.7 Data Analysis and Presentation.

The analysis plan is designed to directly correspond with the specific objectives of this study, ensuring a clear and cohesive approach to investigating the impact attributable to the renewable energy constructs on Kenya’s sectoral performance. Each objective was paired with an appropriate analytical method that allowed for a thorough exploration of the research’s core themes. The first objective was addressed through time series analysis in order to assess the influence of renewable energy constructs on Kenya’s manufacturing sector. Objective Two provided a detailed examination of the influence of renewable energy constructs on Kenya’s service sector while Objective Three provided an analysis of the contribution of renewable energy value chain dynamics on Kenya’s agricultural sector. The empirical results would be used to inform policy recommendations aimed at improving Kenya’s renewable energy infrastructure and supporting sustainable economic development through sectoral acceleration.

3.7.1 Descriptive Statistics

These were utilized to offer an in-depth overview of the data that was exploited. Several descriptive statistics were run to aid in data exploration, data summarization, trend and pattern identification, data distribution assessment, group comparisons, research validity support and visual data presentation. Descriptive statistics are an integral component of a research process as they lay the ground for further complex analyses. The specific statistics include the measures

of central tendency, measures of dispersion, measures of distribution and shape, Position statistics and other measures such as minimum and maximum, count and sum (Gravetter *et al.*, 2021).

3.7.2 Correlation Analysis

Gogtay and Thatte (2017) opines that correlation analysis serves as a critical tool in assessing the direction and magnitude of associations amongst variables without implying causation. This analysis aimed to determine the presence, direction and magnitude of the impact of the renewable constructs on Kenya's sectoral performance. Pearson's coefficient is the most prevalent test for correlation and it ranges from -1 to 1, with 1 indicating the presence of a perfect positive correlation and -1 implying the presence of a perfect negative correlation, while a zero value implies the absence of correlation. The correlation analysis was based on the model as in equation 3.7.

Pearson's correlation coefficient was used to examine the strength and direction of the linear relationship among the study variables. The correlation coefficient was computed using the following expression:

$$r(MVA, SVA, AVA, RET, REG, REC, RNTL, GCF, L) = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{(n\sum x^2 - (\sum x)^2(n\sum y^2 - (\sum y)^2)}} \dots\dots\dots (3.7)$$

Where;

x, y represents any pair of study variables: *MVA, SVA, AVA, RET, REG, REC, RNTL, GCF* and *L.*

r represents the correlation coefficient,

n represents the total sample size,

$\sum$ is the Summation over the study period

Based on the study objectives, the correlation analysis was conducted to test the presence, direction and strength of linear relationships between renewable energy variables and sectoral performance indicators. Accordingly, the study assumed a null hypothesis stating that there is no significant correlation between any of the renewable energy value chain dynamics, that is, installation, generation, consumption as well as transmission-distribution and the sectoral outputs in manufacturing, services and agriculture. The corresponding alternative hypothesis

stated that significant correlations exist between the renewable energy variables and sectoral performance indicators. The analysis aimed to determine whether changes in renewable energy installation, generation, consumption or transmission-distribution losses are significantly associated with changes in the outputs of Kenya's productive sectors. These hypotheses were tested using Pearson's correlation coefficient, which quantifies the strength and direction of linear relationships, with statistical significance evaluated at the 5% level. This approach provides an overarching framework for identifying patterns, trends as well as associations between the renewable energy constructs and sectoral performance, while acknowledging that correlation does not imply causation.

3.7.3 Test for Stationarity

3.7.3.1 Test for stationarity using the Augmented Dickey-Fuller(ADF) Test

The ADF test was exploited to assess whether central tendency, variability and autocorrelation remained stable during the study period. This is because this method is well-suited for handling complex models and offers greater statistical power (Fuller, 2009). Had the variables been identified as non-stationary, it could have resulted in misleading outcomes. Thus, the data needed to be stationary. The stationarity of each variable was evaluated using the formula specified in the equations.

The equation for determining the stationarity using the ADF with a constant was as outlined in equation 3.8. This model includes a constant term only.

$$\Delta Y_t = \alpha + \varphi Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-1} + \varepsilon_t \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots . \dots (3.8)$$

The equation for determining the stationarity using the ADF without a constant was as outlined in equation 3.9. This model does not include a constant term.

$$\Delta Y_t = \varphi Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-1} + \varepsilon_t \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots .. \dots (3.9)$$

The equation for determining the stationarity using the ADF without a constant was outlined in equation 3.10. This model includes both the constant term and the trend term.

$$\Delta Y_t = \alpha + \beta \quad + \varphi Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-1} + \varepsilon_t \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots .. \dots (3.10)$$

Where;

Y_t represents the time series variable, that is, the renewable energy value chain dynamics and sectoral growth elements, α is the intercept term,β_t represents the temporal time trends, φ is the coefficient of the lagged level of the respective sectoral productivities, δ_i is the coefficient of the delayed or lagged differences, p is the number of lagged difference terms within the model, while ε_t represents the error term.

The null hypothesis associated with the ADF test suggests that variables possess a unit root, indicating non-stationarity in the time series, while the alternative hypothesis suggests that the variables are stationary. The t-statistic for the coefficient β is then calculated. Whenever the absolute t-statistic is above the critical limit from the Dickey-Fuller distribution, the null hypothesis should always be rejected, confirming stationarity. Rejecting the null hypothesis indicates stationarity, whereas failure to reject it suggests non-stationarity in the time series.

The ADF test was conducted for each variable individually to determine whether the series were stationary at levels or after first differencing. This step was necessary to ensure that the time series properties of the variables satisfied the requirements for subsequent cointegration and ARDL analysis.

To ensure the suitability of the data for time-series analysis, the stationarity properties of each variable were examined, as non-stationary series can produce unreliable and spurious results in econometric models. The ADF test was employed due to its ability to handle higher-order autocorrelation and provide robust inference for complex datasets. For each variable, the null hypothesis (H_0) suggested that the series possesses a unit root, indicating non-stationarity, whereas the alternative hypothesis (H_1) stated that the series is stationarity, implying stability in its mean and variance over time. The test was applied across multiple specifications, accounting for deterministic components such as constants and trends, to ensure accurate assessment. The calculated t-statistics were compared against critical values from the Dickey-Fuller distribution to determine whether the null hypothesis could be rejected. Establishing stationarity for all variables, including sectoral outputs and renewable energy indicators was essential to meet the prerequisites for cointegration and ARDL analysis, thereby ensuring the reliability and validity of the study's econometric findings.

3.8 Lag Length Selection

Determining the appropriate lag length is a crucial step in time series modeling, particularly in the ARDL framework, where each variable may enter the model with a different number of lags. In this study, lag lengths were selected automatically within the ARDL procedure by the

exploitation of the AIC. A maximum lag length of four was specified, guided by the annual frequency of the data and sample size considerations. The AIC was chosen because of its relative efficiency in small samples and its tendency to select models that balance explanatory power with simplicity. The model selection criteria have been attached in the appendices as Appendices I, K and M. This approach allowed for the identification of optimal lag combinations that best examine the fluctuating associations between the variables while minimizing the inherent risk of overfitting. The selected lag structures were subsequently used in conducting bounds tests for cointegration and estimating the short-term and long-term linkages in the ARDL models (Pesaran & Shin, 1995).

3.9 The Autoregressive Distributed Lag (ARDL) Framework

In line with the primary aim of the study of determining the influence of the various green energy dynamics on Kenya's sectoral performance, the ARDL modeling framework developed by Pesaran and Shin (1995) was employed. This model is appropriate for small-sample historical datasets and can handle variables exhibiting integration of order zero I (0), order one I (1) or a blend of both elements, provided none is second-order integrated, I (2). Stationarity tests conducted earlier confirmed that the series in this study are a mix of I (0) and I (1), thereby justifying the adoption of the ARDL framework.

The ARDL is ideal for this study's objectives as it captures both the immediate and extended term dynamics within a single-equation framework. Unlike multivariate models such as Vector Autoregression (VAR) or Vector Error Correction Models (VECM), which require all variables to be of the same integration order, ARDL allows for variable-specific lag structures. This is particularly important in energy-economy relationships, where effects may manifest at different speeds across sectors. The general ARDL model used in the study is presented below in equation 3.11.

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \beta_i Y_{t-1} + \sum_{j=0}^{q1} \gamma_j LnRET_{t-j} + \sum_{k=0}^{q2} \sum_{l=0}^{q3} \theta_t LnREG_{t-1} + \sum_{n=0}^{q5} \gamma_n REC_{t-n} + \sum_{o=0}^{q6} + \sum_{r=0}^{q7} \theta_r + LnRNTL_{t-r} + \sum_{s=0}^{q8} \beta_s GCF_{t-s} + \sum_{v=0}^{q9} \gamma_v L_{t-v} + \varepsilon_t \quad \text{.....(3.11)}$$

Where Y_t is the logged form of sectoral performance, that is, $LnMVA_t$, $LnSER_t$ and $LnAVA_t$,

$LnRET_t$ is logged renewable energy installation at time t;

REC_t is renewable energy consumption at time t;

$LnREG_t$ is logged renewable energy generation at time t;

$LnRNTL_t$ is logged transmission-distribution losses at time t;

GCF_t is gross capital formation at time t;

L_t is labour at time t while

ε_t is the error term

α_0 is the intercept term

β, γ, δ and *θ* are the coefficients on lags

The ARDL framework sought to estimate how sectoral performance responded to its lags and the lagged effects of the renewable energy installation, generation, consumption, transmission-distribution losses, gross capital formation and labour.

The ARDL framework was complemented with the ECM as well as the bounds test to account for both the transient dynamics and confirmation of enduring equilibrium associations amongst the study variables (Pesaran *et al*., 2001).

To examine both the short-term and long-term dynamics between renewable energy variables and sectoral performance, the study employed the ARDL modeling framework developed by Pesaran and Shin (1995). This approach is suitable for historical time-series data of small to moderate sample size and can accommodate variables integrated of order zero, I (0), order one, I (1) or a combination of both, as long as none are integrated of order two, I (2). Stationarity tests conducted confirmed that the study variables met this requirement, thereby justifying the use of the ARDL approach. The model was designed to estimate how sectoral performance responds to both its own lagged values and the lagged effects of renewable energy installation (RET), generation, consumption and transmission-distribution losses, gross capital formation and labour.

In line with the objectives, the study formulated the following hypotheses for the ARDL analysis: the null hypothesis (H_0) stated that there is no significant short-term or long-term relationship between the renewable energy variables and sectoral performance, while the alternative hypothesis (H_1) asserted that significant relationships exist in either the short or long run. The ARDL framework was complemented by the ECM and bounds testing procedure, which together allowed for the identification of both transient dynamics and the presence of long-run equilibrium relationships among the study variables (Pesaran et al., 2001). This methodology ensures that the influence of renewable energy on sectoral outputs is captured comprehensively, accounting for immediate adjustments as well as sustained effects over time.

3.10 The Error Correction Model (ECM)

The ECM was employed in this study to complement the ARDL framework and provide a robust analysis of both short-run dynamics and the adjustment process toward long-run equilibrium. While ARDL identifies the magnitude and direction of relationships between renewable energy variables and sectoral outputs, ECM captures how deviations from the long-run equilibrium are corrected over time. This approach is suitable for time series data with mixed integration orders, as it allows for a clear distinction between transient fluctuations and enduring relationships, which is critical for understanding the influence of renewable energy installation, generation, consumption and transmission-distribution losses on Kenya's manufacturing, services and agricultural sectors (Engle & Granger, 1987; Pesaran et al., 2001).

The ECM expresses changes in sectoral outputs as a function of short-run changes in renewable energy variables and a lagged error correction term derived from the long-run ARDL relationship. The model represents short-run changes in sectoral output as dependent on contemporaneous and lagged changes in renewable energy value chain dynamics, while the lagged error correction term reflects deviations from long-term equilibrium. A statistically significant and negative coefficient of the error correction term indicates that any disequilibrium is gradually corrected, confirming that short-run shocks are absorbed over time and the system moves back toward equilibrium (Gujarati & Porter, 2009; Pesaran et al., 2001).

The general specification of the ECM applied in this study is expressed by equation 3.12;

$$\Delta Y_t = \alpha + \sum \beta_i \Delta X_{t-i} + \varphi \mathrm{ECT}_{t-1} + \varepsilon_t \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots . (3.12)$$

Where ΔY_t represents the change in sectoral output, specifically manufacturing (MAN), services (SVA) and agriculture (AGR). The term ΔX_{t-i} represents the short-run changes in the explanatory variables, including renewable energy installation (RET), renewable energy generation (REG), renewable energy consumption (REC), transmission-distribution losses (RNTL), gross capital formation (GCF) and labour (L). The term $\varphi \mathrm{ECT}_{t-1}$ represents the lagged error correction term derived from the long-run ARDL relationship and captures the extent of disequilibrium from the previous period. The parameter φ measures the speed of adjustment toward long-run equilibrium, while α represents the intercept and ε_t is the stochastic error term.

The inclusion of ECM in this study ensures a comprehensive understanding of how renewable energy value chain dynamics affect sectoral performance in Kenya. It allows the analysis to differentiate between immediate effects and long-term adjustments, thereby providing deeper

insights into the temporal nature of the renewable energy impacts. By incorporating both short- and long-run dynamics, the ECM enhances the robustness of the econometric analysis and informs effective energy and industrial policy, ensuring that interventions in renewable energy translate into sustainable sectoral performance.

3.10 Bounds Testing for Cointegration

To determine the presence of long-run equilibrium relationships among the study variables, this study employed the Bounds Testing approach as developed by Pesaran et al. (2001). The Bounds test is particularly suitable for small samples and for datasets that include variables integrated of different orders, I(0) or I(1), without requiring all variables to be of the same integration order. This method evaluates whether a set of variables is cointegrated by testing the joint significance of lagged levels of the regressors in an unrestricted error correction model derived from the ARDL specification. The advantage of this approach lies in its ability to provide critical bounds for the F-statistic, enabling inference on long-run relationships regardless of the integration order of the variables (Pesaran et al., 2001).

The Bounds Test compares the computed F-statistic against the lower and upper critical values. If the F-statistic exceeds the upper bound, the null hypothesis of no cointegration is rejected, confirming the existence of a long-run relationship. On the other hand, if the F-statistic falls below the lower bound, the null hypothesis cannot be rejected, implying no cointegration. Values lying between the bounds indicate inconclusive results, requiring further investigation. In this study, the Bounds Test was applied to examine whether renewable energy installation, generation, consumption and transmission-distribution losses maintain a long-term equilibrium association with manufacturing, services and agricultural sector performance. By confirming cointegration, the Bounds Test validates the subsequent estimation of long-run coefficients and ensures that both short-run dynamics captured by the ECM and long-run effects captured by ARDL are grounded in a statistically robust equilibrium framework (Nkoro & Uko, 2016; Pesaran et al., 2001).

To assess the existence of long-run equilibrium relationships among the study variables, the Bounds Testing approach was operationalized through an unrestricted ECM model derived from the ARDL specification. The model tests whether the lagged levels of sectoral output and renewable energy value chain dynamics jointly influence the current changes in output. The equation is specified as in equation 3.13;

$$\Delta Y_t = \alpha_0 + \sum_{i=1}^{p} \beta_i \Delta Y_{t-1} + \sum_{j=0}^{q1} \gamma j \Delta LnRET_{t-j} + \sum_{k=0}^{q2} \delta_k \Delta LnREG_{t-k} + \sum_{l=0}^{q3} \theta_l \Delta REC_{t-1} + \sum_{m=0}^{q4} \emptyset_m \Delta LnRNTL_{t-m} + \lambda_1 Y_{t-1} + \lambda_2 RET_{t-1} + \lambda_3 REG_{t-1} + \lambda_4 REC_{t-1} + \lambda_5 RNTL_{t-1} + \lambda_6 GCF_{t-1} + \lambda_7 L_{t-1} + \varepsilon_t \ldots\ldots (3.13)$$

Where;

Y_t is sectoral output, that is, manufacturing, services and agriculture, at time t;

RET_t is renewable energy installed capacity at time t;

REG_t is renewable energy generation at time t;

REC_t is renewable energy consumption at time t;

$RNTL_t$ is transmission-distribution losses at time t;

GCF_t is gross capital formation at time t;

L_t is labour at time t;

Δ is the difference operator;

α_0 is the intercept;

$\beta_i, \gamma j, \delta_k, \theta_l, \emptyset_m$ and λ_n are the coefficients to be estimated

ε_t is the error term

In this operationalization, the model allows the examination of both short-run dynamics through the differenced terms and the long-run equilibrium relationship through the lagged levels. The F-statistic from this equation is compared against critical bounds to determine whether the null hypothesis of no cointegration can be rejected, thereby validating the existence of enduring relationships between renewable energy value chain dynamics and sectoral performance in Kenya.

The hypotheses for the Bounds Test assess whether a long-run relationship exists between renewable energy value chain dynamics and sectoral performance. The null hypothesis (H_0) states that no cointegration exists among the variables, while the alternative hypothesis (H_1) asserts that a long-run equilibrium relationship is present (Pesaran et al., 2001; Nkoro & Uko, 2016).

3.11 Post Diagnostic Tests

According to Richey and Klein (2014), the analysis and interpretation of data are crucial for deriving meaningful insights that can inform decision-making and policymaking processes. To ensure the reliability of findings, diagnostic and inferential statistics were computed, thereby reducing the risk of obtaining spurious results. To ensure the soundness and dependability of the historical data sources, it was essential to perform pre-diagnostics, which helped enhance confidence in the results and ultimately, the findings of the research. These diagnostic tests included tests for multicollinearity, heteroskedasticity, serial correlation and normality. Statistical significance tests were conducted to determine the criteria for accepting or rejecting the assumed and tested hypotheses as specified.

3.11.1 Test for Autocorrelation

The study conducted a serial autocorrelation analysis to examine the interdependence of error terms across observations. Specifically, the B-G test, as proposed by Breusch (1978) and further elaborated by Breusch and Godfrey (2015), was employed to evaluate the null hypothesis of absence of autocorrelation. This approach was selected because it allows testing beyond simple first-order autocorrelation. The procedure facilitated assessing whether residuals from different data points were statistically independent.

The check for autocorrelation using the B-G test for autocorrelation was done simultaneously using the equations below for the manufacturing, service and agricultural sectors, respectively;

$$\hat{\varepsilon}_t = \alpha + \beta_1 LnRET_t + \beta_2 LnREG_t + \beta_3 REC_t + \beta_4 LnRNTL_t + \gamma_1 GCF_t + \gamma_2 L_t + \delta_1 \hat{\varepsilon}_{t-1} + \delta_2 \hat{\varepsilon}_{t-2} + \cdots + \delta_p \hat{\varepsilon}_{t-p} + \mu_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.14)$$

Where;

$\hat{\varepsilon}_t$ represents the forecast error obtained from the main regression model, while $\hat{\varepsilon}_{t-1}$, $\hat{\varepsilon}_{t-2}$ and $\hat{\varepsilon}_{t-p}$ are the lagged forecast errors from the main model and μ_t represents the error term within the auxiliary regression.

The residuals were lagged to help assess whether past values associated with the residuals are correlated with the recent ones.

The null hypothesis suggested that the coefficients associated with the lagged elements are equal to zero, implying an absence of autocorrelation. A statistically significant result, typically at the 0.05 significance threshold, would indicate existence of serial correlation. The selection of a lag length of one is based on the fact that the dataset under consideration consists of annual data (Stock & Watson, 2015).

3.11.2 Test for Multicollinearity

Multicollinearity is an econometric problem that arises when certain predictors share substantial correlation amongst themselves, complicating the assessment of each variable's impact on the dependent variable (Koop, 2013; Gujarati & Porter, 2009). To detect multicollinearity in this study, a correlation matrix was used, since high pairwise correlations often provide an indication that multicollinearity could exist. To further address potential concerns, the ARDL-ECM employed lagged explanatory variables, which have the capability of capturing dynamic relationships and also help to mitigate collinearity among regressors. Consistent with the assertions of Gujarati & Porter (2009) that not all correlations are harmful, the models were therefore expected to yield stable and reliable coefficient estimates even in the presence of moderate correlation amongst the predictors.

In instances where the R-squared values are excessively high, indicating a potential risk of severe multicollinearity among the independent variables, the study employed the Variance Inflation Factor (VIF) as a diagnostic tool to assess the extent of multicollinearity. The VIF quantifies how much the variance of a regression coefficient is inflated due to correlations among explanatory variables, providing a clear metric for identifying problematic predictors. This approach follows standard econometric practice (Gujarati & Porter, 2009; Kennedy, 2008), ensuring that the regression results remain reliable and that the estimated coefficients are not unduly biased or unstable due to multicollinearity.

The VIF for each independent variable is calculated using the coefficient of determination obtained by regressing that variable on all other explanatory variables, as shown in the equation 3.15;

$$VIF_i = \frac{1}{1 - R_i^2} \quad (3.15)$$

Where R_i^2 is the R-squared derived from regressing the i-th independent variable on all other independent variables.

The null hypothesis for testing multicollinearity among the variables stated that there was no multicollinearity among the independent elements, while the alternative hypothesis suggested that multicollinearity is present.

3.11.3 Test for Heteroskedasticity

Heteroskedasticity arises when the assumptions of constant variance in the error term are violated, which can greatly impact the efficiency of the Ordinary Least Squares estimators. Halunga *et al.* (2017) proposed a test to detect heteroskedasticity, known as the Breusch-Pagan-Godfrey test. This test is regarded as robust because it imposes no constraints and offers greater statistical power compared to alternatives like Durbin's h statistic. Furthermore, it is capable of effectively detecting higher-order serial correlation.

The B-G necessitates a probability statistic of less than 0.05 to lead to the rejection of the null hypothesis. The null hypothesis in this case suggested that the variance of the residuals remains constant, indicating homoscedasticity. If the variance was found to vary, it could suggest the presence of heteroscedasticity.

To assess heteroskedasticity, the Breusch-Pagan-Godfrey test statistic was computed using the Lagrange Multiplier (LM) approach as in equation 3.16;

$$LM = n.R^2 \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots..\dots..(3.16)$$

Where;

LM is the t-statistic which follows a chi-square distribution with k degrees of freedom under the null hypothesis,

n is the number of observations;

R^2 is obtained from regressing the squared residuals of the main regression on the independent variables,

k is the number of explanatory variables in the auxiliary regression, excluding the intercept.

A significant LM statistic with a p-value of less than 0.05 indicates that the null hypothesis of constant variance is rejected, confirming the presence of heteroskedasticity and implying that

corrective measures may be necessary to ensure efficient and unbiased Ordinary Least Squares estimates (Gujarati & Porter, 2009; Halunga et al., 2017).

The study formulated the following hypotheses; the null hypothesis (H_0) stated that the variance of the residuals is constant across all observations, indicating homoscedasticity, while the alternative hypothesis (H_1) asserted that the variance of the residuals is not constant, suggesting the presence of heteroskedasticity. A probability value below 0.05 would lead to the rejection of the null hypothesis, signaling that heteroskedasticity exists and may affect the efficiency of the Ordinary Least Squares estimators. This procedure ensures that the reliability of the regression results is properly evaluated before further econometric analysis.

3.11.4 Normality Test

The Jarque-Bera (J-B) statistical evaluation was exploited in order to assess the spread of the residual values for normality. The test offers a more comprehensive and robust assessment compared to individual tests of skewness and kurtosis. This is because the J-B test combines both measures into a single assessment. The J-B test makes it possible to effectively evaluate whether the residuals exhibit normality, providing valuable insights into the validity of statistical assumptions underlying the analysis. This J-B test evaluated whether the distribution was normal by using the hypothesis asserting that the collected data followed a normal distribution and an alternative hypothesis that the errors deviated from normality. Hence, a J-B value of approximately 3, accompanied by a probability greater than 0.05, would indicate that the residuals followed a normal distribution (Gujarati & Porter,2009).

The J-B statistic for testing normality is computed as in equation 3.17;

$$JB = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.17)$$

Where;

JB is the Jarque-Bera test statistic,

n represents the number of observations,

S is the sample skewness of the residuals,

K is the sample kurtosis of the residuals.

This equation allows for the joint evaluation of skewness and kurtosis in the residuals. Under the null hypothesis(H_0), the residuals are normally distributed, whereas the alternative

hypothesis, (H_1), asserts a deviation from normality. A probability value less than 0.05 leads to the rejection of (H_0) , indicating that the residuals do not follow a normal distribution, which may compromise the validity of statistical inference (Gujarati & Porter, 2009; Nkoro & Uko, 2016).

3.12 The CUSUM (cumulative Sum of Recursive Residuals) Stability Test

In order to guarantee the structural stability associated with the estimated ARDL models, this study employed the CUSUM tests as part of post-estimation diagnostics. CUSUM tests are critical in identifying potential structural breaks and parameter instability over the sample period, which, if found to be present, would likely invalidate the reliability of the model's short-term and long-term projections. According to Brown *et al.* (1975), this test plots the cumulative sum of recursive residuals against critical bounds and if the plot remains within the 5% significance limits, the model would be considered stable. This stability is important for time series models like ARDL, where consistent parameter behaviour over time strengthens the validity of econometric inferences and policy implications and inferences. Therefore, the application of the CUSUM test enhanced the robustness of the results and complemented other classical and primary diagnostic tests such as serial correlation and heteroskedasticity tests.

To assess the structural stability of the estimated models, the CUSUM test was employed. The CUSUM statistic is calculated as in equation 3.18:

$$W_t = \sum_{i=1}^{t} \frac{\hat{\mu}_i}{\sigma} \quad \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \quad (3.18)$$

Where;

W_t is the cumulative sum of recursive residuals up to time t;

$\hat{\mu}_i$ is the recursive residuals derived from the ARDL or ECM models at time i, which depend on sectoral outputs, that is, manufacturing, services and agriculture as well as the renewable energy value chain dynamics renewable energy installation, generation, consumption and transmission-distribution losses;

σ is the is the estimated standard deviation of the residuals from the model.

The null hypothesis (H_0), assumes that the model parameters relating sectoral outputs, manufacturing, services, agriculture, to renewable energy value chain dynamics, renewable energy installed capacity, renewable energy generation, renewable energy consumption and renewable energy transmission-distribution losses are stable over time, while the alternative hypothesis (H_1), suggests structural instability. If the CUSUM plot remains within the 5% significance bounds, the model is considered stable. Deviations outside these bounds indicate parameter instability or potential structural breaks, which could undermine the reliability of both short-run and long-run inferences (Brown et al., 1975; Gujarati & Porter, 2009).

3.13 Data Presentation

The results of these analyses is presented in tables and charts, facilitating clear and concise communication of the findings. This approach ensured that the research outcomes were robust and contributed effectively to informed decision-making and policy formulation (Tufte,1985).

3.14 Potential Limitations and Biases of the Study

This study recognizes a few factors that could have influenced the outcomes and analysis of the results. One such factor is data availability, especially regarding the disaggregation of alternative energies by source. While ample data exists for hydroelectric power, the historical data on other renewable sources like geothermal, solar and wind is less comprehensive. As a result, the study focused on a more generalized analysis of renewable energy value chain dynamics, while still capturing key insights from the disaggregation. The similarities in the dynamics of renewable energy across these sources allow the study to provide meaningful conclusions despite the data limitations.

Another consideration was the potential for variability in how renewable energy installation, generation and consumption were being reported across different sources. To address this, the study relied on well-established and standardized datasets to ensure consistency and alignment with the research objectives. Additionally, given the study's reliance on secondary data, there could have been instances where historical trends were not fully reflective of the current landscape or future developments. However, this limitation was mitigated by focusing on the most recent data available, as well as interpreting findings within the context of evolving renewable energy policies and sectoral dynamics.

Furthermore, while the study primarily focused on Kenya, the findings would have been influenced by country-specific factors related to energy infrastructure and policies. To ensure

a robust analysis, the research drew from a diverse range of data sources, such as government reports from the KNBS, academic studies and independent research, which helped balance potential biases.

Notwithstanding these limitations, this study still offers an important understanding of the dynamics of the influence of the renewable energy value chain dynamics on Kenya's sectoral growth. By focusing on available data and employing rigorous analytical methods, the research contributed to a deeper understanding of how energy value chain can drive sustainable sectoral and overall economic performance in Kenya. Moreover, the strategies employed to address these limitations ensure that the findings remained both relevant and applicable to policy development, providing actionable recommendations for energy stakeholders, not just in Kenya, but to also in economies at the same level of economic performance and energy resource endowments.

3.15 Ethical Considerations

This study exploited secondary data from publicly available and reputable verified sources, that is, the WDI and EIA. The data was used in accordance with ethical research standards, ensuring proper citation and acknowledgment of the sources. The World Bank and the EIA provide datasets under their Open Data Terms of Use, allowing free use with appropriate attribution and following a Data Dissemination and Access Policy that promotes responsible data use. Since this data did not involve human subjects, issues like consent and confidentiality did not apply. However, this study ensured the integrity of the data by using it solely for academic purposes and maintaining accuracy in analysis. The data in this study follows the ethical guidelines set by the World Bank (2016) and EIA (n.d).

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 Introduction

This chapter presents the study findings as per the time series data collected across the 1980-2024 period. It begins with descriptive statistics and correlation analysis to provide an overview of the variables, followed by unit root tests to ascertain their stationarity properties. This chapter then outlines the ARDL-ECM results, supported by diagnostic and stability tests. Each section is analyzed in light of the study objectives and relevant economic theory.

4.2 Descriptive Statistics

Table 4.1 presents the descriptive statistics of the study variables, summarizing their central tendencies, dispersion and overall distribution as well as providing an initial overview of the patterns and characteristics of renewable energy value chain dynamics, sectoral outputs, gross capital formation and labour in Kenya over the study period.

4.2.1 Descriptive Statistics with Raw Data

Table 4.1 Descriptive Statistics

	MVA	AVA	SVA	RET	REC	REG	RNTL	GCF	L
Mean	495.3672	1120.108	2267.897	1003.828	20.30162	1912.970	1155.344	948.7845	8375.140
Median	424.9920	1090.690	1412.411	735.5000	17.00000	666.6900	946.0000	698.7273	6866.800
Maximum	873.8310	1867.490	6639.582	3119.400	42.03780	7498.740	3057.000	1913.160	20844.40
Minimum	227.1424	593.4603	394.5326	313.5000	6.000000	108.0000	249.0000	388.9767	1190.800
Std. Dev.	185.8444	362.4794	1913.143	735.1016	10.65097	2282.809	836.2591	498.0012	6370.173
Skewness	0.463778	0.388903	0.721476	1.679350	0.796064	1.228102	1.053548	0.644762	0.498876
Kurtosis	2.101807	1.947052	2.222466	4.942713	2.434576	2.938956	2.919718	1.889690	1.869999
Jarque-Bera	3.125832	3.213149	5.037508	28.22812	5.352328	11.31874	8.336810	5.429363	4.260771
Probability	0.209524	0.200573	0.080560	0.000001	0.068827	0.003485	0.015477	0.066226	0.118792
Sum	22291.52	50404.85	102055.4	45172.25	913.5728	86083.65	51990.50	42695.30	376881.3
Sum Sq. Dev.	1519679.	5781217.	1.61E+08	23776471	4991.498	2.29E+08	30770487	10912229	1.79E+09
Observations	45	45	45	45	45	45	45	45	45

(Source; Author, 2026)

Table 4.1 presents the descriptive statistics for the sectoral output variables, renewable energy value chain variables, gross capital formation and labour over the study period. Manufacturing value added recorded a mean of Kh 495.367 billion, while agricultural value added averaged Ksh 1, 120.108 billion and services output recorded the highest mean of Ksh 2, 267.897 billion. The higher average output of the services sector relative to agriculture and manufacturing indicates its comparatively larger contribution to Kenya's productive activity over the study

period. The median values of Ksh 424.992 billion for manufacturing, Ksh 1, 090.690 billion for agriculture and Ksh 1,412.411 billion for services are lower than their respective means, indicating positive skewness in the sectoral output distributions. The larger difference between the mean and median for services suggests that relatively high-output observations contributed substantially to its average over the study period.

The renewable energy variables also exhibit considerable variation. Renewable energy installation recorded a mean of 1,003.828MW, compared with a median of 735.500MW, while its maximum value reached 3,119.400MW. The difference between the mean and median indicates that renewable energy installation experienced periods of substantially higher additions. Renewable energy consumption recorded a mean of 20.302MWh and a median of 17.000MWh, with values ranging from 6.000MWh to 42.038MWh. Renewable energy generation recorded a mean of 1,912.970MWh, a median of 666.690MWh and a maximum of 7,498.740MWh, indicating substantial variation and periods of exceptionally high generation. Transmission-distribution losses recorded a mean of 1,155.344MWh, a median of 946.000MWh and a maximum of 3,057.000MWh, indicating considerable variation in electricity-system losses over the study period.

The substantial difference between the mean and median of renewable energy generation is notable. The mean of 1,912.970MWh is considerably higher than the median of 666.690MWh, indicating that a number of relatively high generation observations influenced the average. Also, the mean of transmission-distribution losses exceeds its median, suggesting periods of relatively high electricity-system losses. These patterns demonstrate that renewable energy development in Kenya has been characterized by considerable changes in installation, generation, consumption and transmission-distribution losses over time.

Gross capital formation recorded a mean of Ksh 948.785 billion and a median of Ksh 698.727 billion, with a maximum of Ksh 1, 913.160 billion and a minimum of Ksh 388.977 billion. Labour recorded a mean of 8,375.140 and a median of 6,866.800, with values ranging from 1,190.800 to 2,0844.400. The relatively large standard deviation of labour, that is, 6,370.173, indicates substantial variation in the labour variable over the study period. Similarly, services output recorded a standard deviation of 1,913.143, while renewable energy generation recorded a standard deviation of 2,282.809. These relatively large standard deviations indicate substantial variation in sectoral output and renewable energy value chain variables over time.

The skewness statistics indicate that all variables are positively skewed, with skewness values ranging from 0.389 for agriculture to 1.679 for renewable energy installation. Renewable energy installation has the highest positive skewness at 1.679, followed by renewable energy generation at 1.228 and transmission-distribution losses at 1.054. These values indicate that the distributions of these variables contain relatively more observations concentrated toward the lower values, with some comparatively high observations extending the right-hand tail of the distributions. The positive skewness of the sectoral output variables, Gross capital formation and labour is comparatively moderate, with values of 0.464, 0.389, 0.721, 0.645 and 0.499, respectively.

The kurtosis values provide further information about the shape of the distributions. Renewable energy installation records a kurtosis value of 4.943, which is above the benchmark value of 3.000 for a normal distribution, indicating a leptokurtic distribution with relatively heavier tails and greater concentration around the mean. The kurtosis values for the remaining variables range from 1.870 to 2.939, all below 3.000, indicating relatively flatter distributions compared to the normal distribution. Labour records a kurtosis of 1.870, Gross capital formation at 1.890, agriculture at 1.947, manufacturing at 2.102, services at 2.222, renewable energy consumption at 2.435, transmission-distribution losses at 2.920 and renewable energy generation at 2.939.

The J-B statistics and their associated probability values provide evidence on the normality of the distributions. Manufacturing, agriculture, services, renewable energy consumption, Gross capital formation and labour have probability values of 0.210, 0.201, 0.081, 0.069, 0.066 and 0.119, respectively. These probability values exceed the 0.050 significance level, indicating that the null hypothesis of normality cannot be rejected for these variables. On the other hand, renewable energy installation, renewable energy generation and transmission-distribution losses have probability values of 0.000, 0.003 and 0.015, respectively, which are below 0.050. Therefore, the null hypothesis of normality is rejected for these three variables, indicating statistically significant departures from a normal distribution.

The descriptive statistics reveal variations across sectoral output, renewable energy value chain variables, gross capital formation and labour over the study period. The services sector records the highest average output, while renewable energy generation, installation and transmission-distribution losses exhibit substantial dispersion and positive skewness. The descriptive

evidence therefore suggests that Kenya's renewable energy value chain has been characterized by significant changes in both energy development and system efficiency. These variations provide an important basis for examining the dynamic relationship between renewable energy value chain dynamics and sectoral economic performance.

4.2.1 Descriptive Statistics with Log-Transformed Data

Table 4.2 Descriptive Statistics with Log-Transformed Data

	MVA	AVA	SVA	LNRET	LNREG	REC	LNRNTL	GCF	L
Mean	495.3672	1120.108	2267.897	6.711712	6.819677	20.30162	6.803148	948.7845	8375.140
Median	424.9920	1090.690	1412.411	6.600551	6.502325	17.00000	6.852243	698.7273	6866.800
Maximum	873.8310	1867.490	6639.582	8.045396	8.922490	42.03780	8.025189	1913.160	20844.40
Minimum	227.1424	593.4603	394.5326	5.747799	4.682131	6.000000	5.517453	388.9767	1190.800
Std. Dev.	185.8444	362.4794	1913.143	0.607437	1.261989	10.65097	0.722589	498.0012	6370.173
Skewness	0.463778	0.388903	0.721476	0.639630	0.233019	0.796064	0.059989	0.644762	0.498876
Kurtosis	2.101807	1.947052	2.222466	2.715460	1.909607	2.434576	2.074389	1.889690	1.869999
Jarque-Bera	3.125832	3.213149	5.037508	3.220258	2.636527	5.352328	1.633407	5.429363	4.260771
Probability	0.209524	0.200573	0.080560	0.199862	0.267600	0.068827	0.441886	0.066226	0.118792
Sum	22291.52	50404.85	102055.4	302.0271	306.8855	913.5728	306.1417	42695.30	376881.3
Sum Sq. Dev.	1519679.	5781217.	1.61E+08	16.23510	70.07516	4991.498	22.97396	10912229	1.79E+09
Observations	45	45	45	45	45	45	45	45	45

(Source; Author, 2026)

Descriptive statistics are presented in Table 4.2 for the transformed variables used in the subsequent estimations to ensure consistency between the preliminary data analysis and the econometric specification. The use of transformed data is important because renewable energy installation, generation and transmission-distribution losses enter the empirical models in logarithmic form, while renewable energy consumption, gross capital formation, labour and the sectoral output variables are retained in levels. Presenting the descriptive statistics for the variables in their estimation form therefore provides a more appropriate assessment of the distributions actually used in the analysis. It also maintains consistency between the descriptive analysis and the subsequent econometric specification.

Table 4.2 presents the descriptive statistics for manufacturing value added, agricultural value added, services output, logged renewable energy installation, logged renewable energy generation, renewable energy consumption, logged transmission-distribution losses, gross capital formation and labour. The statistics cover 45 annual observations and report measures of central tendency, dispersion, range and distributional shape, together with the J-B test of normality.

Manufacturing value added has a mean of Ksh 495.367 billion, while its median is Ksh 424.992 billion. The mean being higher than the median indicates some degree of positive asymmetry, consistent with the positive skewness of 0.464. Manufacturing value added ranges from a minimum of Ksh 227.142 billion to a maximum of Ksh 873.831 billion, while its standard deviation is Ksh 185.844 billion, indicating considerable variation around the mean. The kurtosis of 2.102, which is below the normal-distribution benchmark of 3.000, indicates a relatively flatter distribution. The J-B statistic is 3.126, with a probability value of 0.210. Since the probability exceeds the 5% significance level, the null hypothesis of normality is not rejected.

Agricultural value added records a mean of Ksh 1,120.108 billion and a median of Ksh 1,090.690 billion, showing relatively close central values. The variable ranges from Ksh 593.460 billion to Ksh 1,867.490 billion, while its standard deviation is Ksh 362.479 billion. The skewness coefficient of 0.389 indicates mild positive asymmetry, with the mean slightly exceeding the median. Its kurtosis of 1.947 indicates a relatively flat distribution compared to the normal benchmark. The J-B statistic of 3.213 has a probability value of 0.201, which is above 0.050. Thus, the null hypothesis of normality cannot be rejected.

Services output exhibits the largest dispersion among the three productive-sector output measures. Its mean is Ksh 2,267.897 billion, compared with a median of Ksh 1,412.411 billion. The substantial difference between the mean and median is consistent with the positive skewness of 0.721. Services output ranges from Ksh 394.533 billion to Ksh 6,639.582 billion, with a standard deviation of Ksh 1,913.143 billion. The wide range and large standard deviation indicate substantial variation in services output over the study period. The kurtosis of 2.222 is below 3.000, indicating a relatively flatter distribution than the normal distribution. The J-B statistic of 5.038 has a probability value of 0.081. Therefore, the null hypothesis of normality cannot be rejected at the 5% level.

The logarithm of renewable energy installation has a mean of 6.712 and a median of 6.601. Since the variable is expressed in logarithmic form, these statistics describe the distribution of the transformed installation series rather than renewable energy installation in its original physical unit. The log-transformed series ranges from 5.748 to 8.045, with a standard deviation of 0.607. Its skewness of 0.640 indicates moderate positive asymmetry, while the kurtosis of 2.715 is relatively close to the normal benchmark of 3.000. The J-B statistic is 3.220, with a probability value of 0.200, indicating that the null hypothesis of normality cannot be rejected at the 5% level.

The logarithm of renewable energy generation has a mean of 6.820 and a median of 6.502. These statistics refer to the log-transformed generation series and should therefore not be analyzed directly in the original physical units of energy generation. The log-transformed variable ranges from 4.682 to 8.922, with a standard deviation of 1.262, indicating greater dispersion than the transformed installation series. The skewness of 0.233 indicates mild positive asymmetry, while the kurtosis of 1.910 suggests a relatively flat distribution. The J-B statistic is 2.637, with a probability value of 0.268, which is above 0.050. Therefore, the null hypothesis of normality cannot be rejected.

Renewable energy consumption, which is retained in levels in the models has a mean of 20.302MWh and a median of 17.000MWh. The difference between the mean and median, together with the skewness coefficient of 0.796, indicates moderate positive asymmetry. Renewable energy consumption ranges from 6.000 to 42.038, while its standard deviation is 10.651, indicating substantial variation over the study period. The kurtosis of 2.435 is below 3.000, suggesting a relatively flat distribution. The J-B statistic is 5.352, with a probability value of 0.069. Since this exceeds 0.050, the null hypothesis of normality is not rejected at the 5% level.

The logarithm of renewable energy transmission-distribution losses has a mean of 6.803 and a median of 6.852. Because the variable is log-transformed, these statistics describe the distribution of the transformed loss series. Its values range from 5.517 to 8.025, while the standard deviation is 0.723. The skewness coefficient of 0.060 is very close to zero, indicating an approximately symmetric distribution. Its kurtosis of 2.074 is below the normal benchmark

of 3.000, suggesting a relatively flat distribution. The J-B statistic of 1.633 and probability value of 0.442 provide no evidence against normality at the 5% level.

Gross capital formation has a mean of Ksh 948.785 billion and a median of Ksh 698.727 billion. The mean exceeding the median, together with skewness of 0.645, indicates moderate positive asymmetry. The variable ranges from Ksh 388.977 billion to Ksh 1,913.160 billion, with a standard deviation of Ksh 498.001 billion, demonstrating substantial variation in gross capital formation over the study period. The kurtosis of 1.890 indicates a relatively flat distribution. The J-B statistic of 5.429 has a probability value of 0.066, which is above the 5% significance level. Thus, the null hypothesis of normality is not rejected at the conventional 5% level.

Labour records a mean of 8,375.140 and a median of 6,866.800, with values ranging from 1,190.800 to 2,0844.400. Its standard deviation of 6,370.173 indicates substantial variation over the study period. The mean being above the median is consistent with the positive skewness coefficient of 0.499, indicating moderate rightward asymmetry. The kurtosis of 1.870 indicates a relatively flat distribution. The J-B statistic of 4.261 has a probability value of 0.119, which exceeds 0.050. Therefore, the null hypothesis of normality is not rejected for labour.

The descriptive statistics indicate that the log-transformed variables exhibit moderate dispersion and predominantly positive but relatively mild skewness, with skewness coefficients ranging from 0.060 for logged transmission-distribution losses to 0.796 for renewable energy consumption. All variables have kurtosis values below the normal benchmark of 3.000, indicating relatively flatter distributions rather than excessively peaked distributions. The J-B probability values for all variables exceed 0.050. Thus, the null hypothesis of normality is not rejected for any of the variables at the conventional 5% significance level.

The differences in dispersion across the variables also reflect their distinct scales and economic characteristics. Services output displays the greatest absolute variation among the sectoral output measures, with a standard deviation of 1,913.143, while agricultural value added records a standard deviation of 362.479 and manufacturing value added 185.844. Among the log-transformed renewable-energy value chain variables, renewable energy generation has the largest standard deviation at 1.262, compared with 0.607 for renewable energy installation and 0.723 for transmission-distribution losses.

The descriptive evidence therefore provides a useful preliminary characterization of the variables entering the subsequent econometric analysis. The use of the log-transformed variables ensures that the descriptive statistics correspond directly to the variables employed in the subsequent model specifications and analysis. The J-B results further indicate that none of the variables exhibits a statistically significant departure from normality at the 5% level.

4.3 Correlation Analysis

Correlation analysis was conducted to examine the strength and direction of relationships between renewable energy variables, gross capital formation, labour and sectoral outputs, providing preliminary insights that guide the subsequent regression analysis.

4.3.1 Correlation Analysis, Manufacturing

Table 4.3 Correlation Analysis with Log-Transformed Data: Manufacturing

Date: 03/17/26 Time: 13:52
Sample: 1981 2024
Included observations: 44

Correlation t-Statistic Probability	MVA	LNRET	LNREG	REC	LNRNTL	GCF	L
MVA	1.000000						

LNRET	0.238695	1.000000					
	1.592965	-----					
	0.1187	-----					
LNREG	0.116671	0.071469	1.000000				
	0.761315	0.464361	-----				
	0.4507	0.6448	-----				
REC	0.149036	0.149206	0.067862	1.000000			
	0.976775	0.977912	0.440815	-----			
	0.3343	0.3337	0.6616	-----			
LNRNTL	-0.073944	-0.161716	0.112896	-0.277281	1.000000		
	-0.480529	-1.062017	0.736357	-1.870326	-----		
	0.6333	0.2943	0.4656	0.0684	-----		
GCF	0.233354	-0.043599	0.157546	0.144140	0.187195	1.000000	
	1.555246	-0.282820	1.033930	0.943989	1.234995	-----	
	0.1274	0.7787	0.3071	0.3506	0.2237	-----	
L	0.445770	0.184511	0.152955	-0.047802	0.049614	0.092804	1.000000
	3.227311	1.216655	1.003066	-0.310145	0.321931	0.604048	-----
	0.0024	0.2305	0.3216	0.7580	0.7491	0.5491	-----

(Source; Author, 2026)

Table 4.3 presents the Pearson correlation coefficients among the variables employed in the manufacturing sector model using the log-transformed data. The transformation is consistent with the functional form adopted in the subsequent ARDL estimation, in which renewable

energy installation, renewable energy generation and transmission-distribution losses are expressed in natural logarithms, while manufacturing value added, renewable energy consumption, gross capital formation and labour remain in their original forms. Conducting the correlation analysis using the same log-transformed variables as those entering the estimated model provides a consistent preliminary assessment of the linear relationships among the variables.

The correlation analysis provides an initial indication of the direction and strength of the association between manufacturing value added and the renewable energy variables and other control variables. It also provides an initial screening for possible multicollinearity among the explanatory variables. However, correlation coefficients measure pairwise linear association and should not be regarded as evidence of causality. Also, relatively high pairwise correlation does not by itself establish problematic multicollinearity, since multicollinearity concerns the joint linear relationship among explanatory variables.

The results show that manufacturing value added has a positive but weak correlation with renewable energy installation, with a correlation coefficient of 0.239, suggesting a modest positive linear association between renewable energy installation and manufacturing output. The correlation between manufacturing value added and renewable energy generation is also positive but weak, with a coefficient of 0.117, while the association between manufacturing value added and renewable energy consumption is positive, with a coefficient of 0.149. These coefficients indicate that manufacturing output tends to move in the same direction as renewable energy installation, generation and consumption, although the pairwise relationships are relatively weak.

Manufacturing value added exhibits a weak negative correlation with transmission-distribution losses, with a coefficient of −0.074, indicating a slight inverse association between manufacturing output and transmission-distribution losses. This direction of association is economically plausible because higher energy losses may reduce the amount of electricity effectively available to productive activities. However, the magnitude of the coefficient is small, indicating a limited pairwise linear association. Manufacturing value added is positively correlated with gross capital formation, with a coefficient of 0.233 and more strongly correlated with labour, with a coefficient of 0.446, suggesting that gross capital formation and labour have

stronger pairwise associations with manufacturing output than some of the renewable energy value chain variables.

Among the explanatory variables, the correlation between renewable energy installation and renewable energy generation is very weak, with a coefficient of 0.071, while renewable energy installation and renewable energy consumption are also weakly correlated, with a coefficient of 0.149. Renewable energy installation has a weak negative correlation with transmission-distribution losses, with a coefficient of −0.162 and a near-zero negative correlation with gross capital formation, with a coefficient of −0.044. Its correlation with labour is positive but weak, at 0.185. These results suggest limited pairwise linear association between renewable energy installation and the other explanatory variables.

Renewable energy generation displays a weak positive correlation with renewable energy consumption, with a coefficient of 0.068, transmission-distribution losses, with a coefficient of 0.113 and labour, with a coefficient of 0.153. Its correlation with gross capital formation is weakly negative, at −0.044. The relatively low magnitudes indicate that renewable energy generation does not exhibit strong pairwise linear relationships with the other explanatory variables in the manufacturing model.

Renewable energy consumption has a weak negative correlation with transmission-distribution losses, with a coefficient of −0.277 and weak positive correlations with gross capital formation and labour, with coefficients of 0.158 and 0.093, respectively. The negative association between renewable energy consumption and transmission-distribution losses is consistent with the possibility that greater energy utilization is associated with lower energy losses. However, this correlation does not establish a causal relationship.

The correlation between transmission-distribution losses and gross capital formation is positive but weak, with a coefficient of 0.187, while the association between transmission-distribution losses and labour is very weak, with a coefficient of 0.050. Gross capital formation and labour also exhibit a weak positive correlation, with a coefficient of 0.093. The explanatory variables display low pairwise correlations, with no exceptionally high correlation coefficient evident in the manufacturing specification.

The reported probability values show that the correlation between manufacturing value added and labour is statistically significant at the 5% level with a p-value of 0.002. The remaining pairwise correlations are statistically insignificant at the 5% level, as their probability values exceed 0.050. Thus, although labour has a statistically significant positive pairwise association with manufacturing value added, the correlation analysis does not provide evidence of widespread statistically significant pairwise relationships among the variables.

Correlation analysis is used only as an initial multicollinearity screening procedure rather than as the sole diagnostic. Where relatively high absolute correlation magnitudes are identified across the sectoral models, VIF diagnostics are subsequently undertaken to provide a more formal assessment of potential multicollinearity among the explanatory variables. This additional diagnostic is important because pairwise correlation examines variables two at a time, whereas VIF assesses the extent to which an explanatory variable can be explained by the combined linear influence of the remaining explanatory variables.

The correlation results therefore provide preliminary evidence of generally low pairwise associations among the variables used in the manufacturing model. The relatively weak correlations between the renewable energy indicators and the other explanatory variables suggest that there are no immediate indications of severe pairwise multicollinearity. The subsequent VIF diagnostics provide an additional and more formal basis for determining whether multicollinearity poses a serious concern for the ARDL estimation.

4.3.2 Correlation Analysis, services

Table 4.4 Correlation Analysis with Log-Transformed Data, services

Date: 03/17/26 Time: 13:54
Sample: 1981 2024
Included observations: 44

Correlation t-Statistic Probability	SVA	LNRET	LNREG	REC	LNRNTL	GCF	L
SVA	1.000000						

LNRET	0.173993	1.000000					
	1.145073	-----					
	0.2587	-----					
LNREG	0.103465	0.071469	1.000000				
	0.674148	0.464361	-----				
	0.5039	0.6448	-----				

REC	0.146154	0.149206	0.067862	1.000000			
	0.957467	0.977912	0.440815	-----			
	0.3438	0.3337	0.6616	-----			
LNRNTL	-0.041496	-0.161716	0.112896	-0.277281	1.000000		
	-0.269158	-1.062017	0.736357	-1.870326	-----		
	0.7891	0.2943	0.4656	0.0684	-----		
GCF	0.183684	-0.043599	0.157546	0.144140	0.187195	1.000000	
	1.211015	-0.282820	1.033930	0.943989	1.234995	-----	
	0.2327	0.7787	0.3071	0.3506	0.2237	-----	
L	0.684301	0.184511	0.152955	-0.047802	0.049614	0.092804	1.000000
	6.081710	1.216655	1.003066	-0.310145	0.321931	0.604048	-----
	0.0000	0.2305	0.3216	0.7580	0.7491	0.5491	-----

(Source; Author, 2026)

Table 4.4 presents the Pearson correlation coefficients among the variables included in the services-sector model. The analysis is based on the log-transformed variables used in the subsequent ARDL estimation. Renewable energy installation, renewable energy generation transmission-distribution losses are expressed in natural logarithms, while services output, renewable energy consumption, gross capital formation and labour are retained in levels. Using the same functional forms in the correlation analysis and subsequent econometric estimation ensures consistency in the preliminary assessment of the relationships among the variables.

The correlation analysis provides preliminary evidence on the direction and strength of the linear associations between services-sector output and the explanatory variables. It also provides an initial assessment of possible multicollinearity among the explanatory variables. However, correlation coefficients measure pairwise linear association and should not be treated as evidence of causality. Also, the magnitude of a pairwise correlation alone is insufficient to establish problematic multicollinearity, which is more appropriately assessed using joint diagnostics such as the VIF.

Services-sector output exhibits a weak positive correlation with renewable energy installation, with a coefficient of 0.174 and a probability value of 0.259. The relationship is statistically insignificant at the 5% level. Similarly, the correlation between services output and renewable energy generation is weakly positive, with a coefficient of 0.103 and a probability value of 0.504, indicating no statistically significant pairwise association. Renewable energy consumption also has a weak positive correlation with services output, with a coefficient of 0.146 and a probability value of 0.344. The correlation between services output and

transmission-distribution losses is weakly negative, with a coefficient of −0.041 and a probability value of 0.789. Similarly, the correlation between services output and gross capital formation is weakly positive, with a coefficient of 0.184 and a probability value of 0.233. None of these relationships is statistically significant at the 5% level.

Services-sector output has a relatively strong positive correlation with labour, with a coefficient of 0.684 and a probability value of 0.000. This statistically significant association indicates that higher labour levels are strongly associated with higher services-sector output. The relationship is economically plausible because labour constitutes an important input in many service-sector activities. However, this correlation should be treated as an association rather than a causal effect. Furthermore, because services output is the dependent variable, its correlation with labour does not constitute evidence of multicollinearity among the explanatory variables.

The correlations among the renewable energy variables and the other explanatory variables are generally weak. Renewable energy installation has a weak positive correlation with renewable energy generation, with a coefficient of 0.071 and a probability value of 0.645. Its correlation with renewable energy consumption is also weakly positive, with a coefficient of 0.149 and a probability value of 0.334. Renewable energy installation has a weak negative correlation with transmission-distribution losses, with a coefficient of −0.162 and a probability value of 0.294. Its association with gross capital formation is very weakly negative, with a coefficient of −0.044 and a probability value of 0.779, while its correlation with labour is weakly positive, with a coefficient of 0.185 and a probability value of 0.231. These findings indicate that renewable energy installation has limited pairwise linear association with the other explanatory variables.

Renewable energy generation is weakly correlated with renewable energy consumption, with a coefficient of 0.068 and a probability value of 0.662. Its correlation with transmission-distribution losses is also weakly positive, with a coefficient of 0.113 and a probability value of 0.466. Also, renewable energy generation has weak positive correlations with gross capital formation and labour, with coefficients of 0.158 and 0.153, respectively and probability values of 0.307 and 0.322, respectively. All these relationships are statistically insignificant at the 5% level, indicating limited contemporaneous pairwise association between renewable energy generation and the other explanatory variables.

Renewable energy consumption has a weak negative correlation with transmission-distribution losses, with a coefficient of −0.277 and a probability value of 0.068. Although this represents the largest absolute correlation among the explanatory variables in the services-sector model, it remains statistically insignificant at the 5% level. The negative association may suggest that higher renewable energy consumption tends to coincide with lower transmission-distribution losses; however, the correlation does not provide sufficient evidence to establish a causal relationship. Renewable energy consumption also has a weak positive correlation with gross capital formation, with a coefficient of 0.144 and a probability value of 0.351, while its correlation with labour is very weakly negative, with a coefficient of −0.048 and a probability value of 0.758.

Transmission-distribution losses have a weak positive correlation with gross capital formation, with a coefficient of 0.187 and a probability value of 0.224 and an almost negligible positive correlation with labour, with a coefficient of 0.050 and a probability value of 0.749. Gross capital formation and labour also exhibit a weak positive correlation, with a coefficient of 0.093 and a probability value of 0.549. These results indicate that the explanatory variables generally exhibit low pairwise correlations.

The correlation matrix provides no evidence of exceptionally strong pairwise correlations among the explanatory variables in the services-sector model. The largest absolute correlation among the explanatory variables is 0.277 between renewable energy consumption and transmission-distribution losses, which is relatively low. This provides preliminary evidence that severe pairwise multicollinearity is unlikely to be a major concern in the services-sector specification.

Correlation analysis alone cannot conclusively rule out multicollinearity because it examines relationships between variables on a pairwise basis and does not capture their joint linear relationships. Therefore, VIF diagnostics were subsequently employed to provide a more comprehensive assessment of multicollinearity among the explanatory variables. The VIF results complement the correlation analysis by determining whether any explanatory variable is substantially explained by the combined influence of the remaining regressors.

The correlation analysis indicates that the renewable energy value chain variables, gross capital formation and labour generally exhibit weak pairwise associations with one another in the

services-sector model. The only relatively strong relationship involving the dependent variable is between services output and labour, with a correlation coefficient of 0.684 and a probability value of 0.000, while the explanatory variables themselves remain weakly correlated. These findings provide preliminary support for their simultaneous inclusion in the services-sector ARDL framework, subject to confirmation from the subsequent VIF diagnostics.

4.3.2 Correlation Analysis, Agriculture

Table 4.5 Correlation Analysis with Log-Transformed Data, Agriculture

Date: 03/17/26 Time: 13:53
Sample: 1981 2024
Included observations: 44

Correlation
SSCP
Probability

	AVA	LNRET	LNREG	REC	LNRNTL	GCF	L
AVA	1.000000						
	78730.08						

LNRET	-0.090833	1.000000					
	-14.25045	0.312631					
	0.5576	-----					
LNREG	-0.201225	0.071469	1.000000				
	-73.14212	0.051767	1.678149				
	0.1903	0.6448	-----				
REC	0.091810	0.149206	0.067862	1.000000			
	207.2612	0.671212	0.707297	64.73145			
	0.5534	0.3337	0.6616	-----			
LNRNTL	0.022250	-0.161716	0.112896	-0.277281	1.000000		
	4.033271	-0.058414	0.094481	-1.441210	0.417347		
	0.8860	0.2943	0.4656	0.0684	-----		
GCF	0.309538	-0.043599	0.157546	0.144140	0.187195	1.000000	
	47324.75	-13.28292	111.2061	631.8963	65.89434	296899.4	
	0.0409	0.7787	0.3071	0.3506	0.2237	-----	
L	0.024631	0.184511	0.152955	-0.047802	0.049614	0.092804	1.000000
	15904.35	237.4081	455.9715	-885.0333	73.75808	116367.4	5295617.
	0.8739	0.2305	0.3216	0.7580	0.7491	0.5491	-----

(Source; Author, 2026)

The correlation analysis in Table 4.5 presents the Pearson correlation coefficients among the variables used in the agriculture sector model. The analysis employs the same log-transformed variables used in the subsequent ARDL estimation for consistency. Renewable energy installation, renewable energy generation and transmission-distribution losses are expressed in natural logarithmic form, while agricultural value added, renewable energy consumption, gross capital formation and labour are retained in their original levels. The correlation analysis

provides preliminary evidence on the direction and strength of the linear associations among the variables and serves as an initial diagnostic for potential multicollinearity among the explanatory variables.

Agricultural value added has a weak negative correlation with renewable energy installation, with a correlation coefficient of -0.091 and a probability value of 0.558. This indicates a very weak inverse linear association that is statistically insignificant at the 5% level. Agricultural value added also has a weak negative correlation with renewable energy generation, with a coefficient of -0.201 and a probability value of 0.190. This suggests that agricultural output and renewable energy generation move in opposite directions in the pairwise correlation, although the relationship is not statistically significant. Renewable energy consumption has a weak positive correlation with agricultural value added, with a coefficient of 0.092 and a probability value of 0.553, indicating a limited and statistically insignificant linear association. Transmission-distribution losses have an almost negligible positive correlation with agricultural value added, with a coefficient of 0.022 and a probability value of 0.874.

Gross capital formation exhibits the strongest correlation with agricultural value added among the explanatory variables, with a coefficient of 0.310 and a probability value of 0.041. This represents a weak positive and statistically significant association at the 5% level, suggesting that agricultural output tends to increase alongside higher levels of gross capital formation. However, the correlation should be treated as a pairwise association rather than evidence of a causal effect. Labour has an almost negligible positive correlation with agricultural value added, with a coefficient of 0.025 and a probability value of 0.874, indicating no statistically significant linear association.

Among the explanatory variables, renewable energy installation has a very weak positive correlation with renewable energy generation, with a coefficient of 0.071 and a probability value of 0.645. Its correlation with renewable energy consumption is also weakly positive, with a coefficient of 0.149 and a probability value of 0.334. Renewable energy installation has a weak negative correlation with transmission-distribution losses, with a coefficient of -0.162 and a probability value of 0.294. Its correlation with gross capital formation is very weakly negative, with a coefficient of -0.044 and a probability value of 0.779, while its correlation with labour is weakly positive at 0.185 with a probability value of 0.231. These results indicate

that renewable energy installation has relatively limited pairwise linear associations with the other explanatory variables.

Renewable energy generation has a very weak positive correlation with renewable energy consumption, with a coefficient of 0.068 and a probability value of 0.662. Its correlation with transmission-distribution losses is weakly positive at 0.113, with a probability value of 0.466. Renewable energy generation has a very weak negative correlation with gross capital formation, with a coefficient of -0.044 and a probability value of 0.779, while its correlation with labour is weakly positive at 0.153 and has a probability value of 0.322. These relatively small coefficients indicate limited pairwise linear association between renewable energy generation and the other explanatory variables.

Renewable energy consumption has a weak negative correlation with transmission-distribution losses, with a coefficient of -0.277 and a probability value of 0.068. Although this is among the larger absolute correlations between the explanatory variables, it remains statistically insignificant at the 5% level. The negative association suggests that higher renewable energy consumption tends to be associated with lower transmission-distribution losses in the pairwise data, although the correlation does not infer causality. Renewable energy consumption also has a weak positive correlation with gross capital formation, with a coefficient of 0.144 and a probability value of 0.351. Its correlation with labour is very weak and negative at -0.048, with a probability value of 0.758.

Transmission-distribution losses have a weak positive correlation with gross capital formation, with a coefficient of 0.187 and a probability value of 0.224. Their correlation with labour is negligible at 0.050, with a probability value of 0.749. Gross capital formation and labour also exhibit a weak positive correlation, with a coefficient of 0.093 and a probability value of 0.549. The explanatory variables display relatively low pairwise correlations, with the largest absolute correlation being 0.277 between renewable energy consumption and transmission-distribution losses.

The correlation matrix therefore provides no evidence of strong pairwise linear relationships among the explanatory variables in the agriculture sector model. The relatively low correlation coefficients suggest that the renewable energy value chain variables, gross capital formation and labour capture sufficiently distinct dimensions of the agricultural production process.

However, correlation analysis considers variables only in pairs and therefore cannot conclusively establish the absence of multicollinearity arising from the joint relationship among several explanatory variables.

Therefore, VIF diagnostics were subsequently employed as an additional and more robust assessment of multicollinearity among the explanatory variables. The use of VIF alongside the correlation analysis provides a more comprehensive diagnostic because it evaluates the extent to which each explanatory variable can be explained by the combined linear influence of the remaining explanatory variables. This strengthens the assessment of whether multicollinearity presents a serious concern for the estimation and analysis of the agriculture sector ARDL model.

The correlation results indicate that agricultural value added has relatively weak pairwise associations with the renewable energy value chain variables. The statistically significant positive correlation between agricultural value added and gross capital formation provides preliminary evidence of an association between investment and agricultural sector performance. However, the renewable energy variables do not exhibit statistically significant pairwise correlations with agricultural value added at the 5% level. These findings should be regarded as preliminary descriptive evidence, with the dynamic and potentially lagged relationships between renewable energy value chain and agricultural output being assessed subsequently through the ARDL-ECM estimations.

4.4 Stationarity Test: The Augmented Dickey-Fuller(ADF) Unit Root Test

Before estimating the relationships among renewable energy variables, gross capital formation, labour and sectoral output, it is necessary to establish the stationarity properties of the time-series variables. Testing for unit roots is important because the use of non-stationary variables in regression analysis may produce spurious relationships. The ADF unit root test was therefore applied to determine the order of integration of each variable.

Table 4.5 ADF Stationarity Test Results

Variable	Level	First Difference	Order of integration
MVA	-5.979840 (0.0001)		I(0)
AVA	-4.914342 (0.0015)		I(0)
SVA	-5.128544 (0.0007)		I(0)
LNRET	-6.969825 (0.0000)		I(0)
LNREG	-9.429989 (0.0000)		I(0)
REC	-6.989332 (0.0000)		I(0)
LNRNTL	-8.328241 (0.0000)		I(0)

GCF	-5.960494 (0.0001)		I(0)
L	-3.437801 (0.0631)	-3.825047 (0.0269)	I(1)

(Source; Author, 2026)

The ADF test results in Table 4.6 indicate that the variables exhibit mixed orders of integration, with most variables stationary at level and labour becoming stationary after first differencing. This pattern supports the suitability of the ARDL modelling framework, which permits the analysis of variables integrated of order zero and order one.

Manufacturing value added, agricultural value added and services output are stationary at levels. The ADF test statistics are -5.980, -4.914 and -5.129, respectively, with probability values of 0.000, 0.002 and 0.001. Since all probability values are below the 5% significance level, the null hypothesis of a unit root is rejected for each variable. Thus, manufacturing value added, agricultural value added and services are integrated of order zero, I(0).

The renewable energy value chain variables are also stationary at levels. Renewable energy installation has an ADF test statistic of -6.970 with a probability value of 0.000, while renewable energy generation records an ADF statistic of -9.430 with a probability value of 0.000. Renewable energy consumption has an ADF statistic of -6.989 with a probability value of 0.000, while the log of transmission-distribution losses has an ADF statistic of -8.328 with a probability value of 0.000. Since all probability values are below 0.050, the null hypothesis of a unit root is rejected for all four renewable energy value chain variables. The logs of renewable energy installation, generation, transmission-distribution losses and renewable energy consumption are integrated of order zero, I(0).

Gross capital formation is similarly stationary at level. Its ADF test statistic is -5.960 with a probability value of 0.000. The probability value is below the 5% significance level, leading to rejection of the null hypothesis of a unit root. Gross capital formation is therefore integrated of order zero, I(0).

Labour exhibits a different stationarity pattern. At level, the ADF test statistic is -3.438 with a probability value of 0.063. Since the probability value exceeds the 5% significance level, the null hypothesis of a unit root cannot be rejected, indicating that labour is non-stationary at level. After first differencing, the ADF test statistic becomes -3.825 with a probability value of 0.027. The probability value is below 0.050, leading to rejection of the unit-root null

hypothesis. Labour is therefore stationary after first differencing and is classified as integrated of order one, I(1).

The ADF results demonstrate that the variables are either I(0) or I(1), with none integrated of order two, I(2). This satisfies the integration-order requirement for applying the ARDL bounds testing approach. The presence of a mixture of I(0) and I(1) variables makes the ARDL-ECM framework appropriate for examining both the short-run and long-run relationships among renewable energy value chain dynamics and productive-sector output.

4.5 Autoregressive Distributed Lag (ARDL) Analysis

The ARDL analysis examines how renewable energy variables, gross capital formation and labour dynamically influence sectoral output, highlighting both immediate and delayed effects.

4.5.1 Renewable Energy Value Chain Dynamics and Manufacturing Sector

4.5.1.1 Renewable Energy Value Chain Dynamics and Manufacturing Sector, ARDL Analysis

Table 4.6 ARDL Analysis, Manufacturing

Dependent Variable: MVA
Method: ARDL
Date: 03/17/26 Time: 15:18
Sample (adjusted): 1985 2024
Included observations: 40 after adjustments
Maximum dependent lags: 1 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): REC LNRET LNREG LNRNTL GCF L
Fixed regressors: C
Number of models evaluated: 15625
Selected Model: ARDL(1, 4, 4, 4, 4, 2, 1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
MVA(-1)	0.147731	0.131847	1.120473	0.2828
REC	2.230854	1.351097	1.651143	0.1226
REC(-1)	1.010286	1.359246	0.743269	0.4705
REC(-2)	-0.481839	1.627734	-0.296018	0.7719
REC(-3)	6.517148	1.523629	4.277384	0.0009
REC(-4)	1.724612	1.234552	1.396954	0.1858
LNRET	4.362119	25.25994	0.172689	0.8656
LNRET(-1)	-16.39872	20.48102	-0.800679	0.4377
LNRET(-2)	-14.55075	17.27547	-0.842278	0.4149
LNRET(-3)	44.40522	19.08793	2.326351	0.0368
LNRET(-4)	34.42419	20.35584	1.691121	0.1146
LNREG	0.041944	7.177500	0.005844	0.9954
LNREG(-1)	10.05589	10.41663	0.965369	0.3520
LNREG(-2)	24.55418	8.184571	3.000058	0.0102
LNREG(-3)	-15.85381	8.086985	-1.960411	0.0717
LNREG(-4)	-22.49441	7.857431	-2.862820	0.0133
LNRNTL	-25.49819	13.77415	-1.851163	0.0870

LNRNTL(-1)	-14.47721	16.57102	-0.873646	0.3982
LNRNTL(-2)	-37.27801	20.30159	-1.836211	0.0893
LNRNTL(-3)	-33.06196	17.11422	-1.931841	0.0755
LNRNTL(-4)	-48.31841	16.37091	-2.951479	0.0112
GCF	0.041879	0.015157	2.762978	0.0161
GCF(-1)	0.056699	0.019985	2.837122	0.0140
GCF(-2)	0.024138	0.019021	1.269056	0.2267
L	0.020166	0.005195	3.881732	0.0019
L(-1)	-0.031727	0.005091	-6.231619	0.0000
C	11.63913	3.911826	2.975370	0.0107

R-squared	0.947024	Mean dependent var	15.28934
Adjusted R-squared	0.841072	S.D. dependent var	14.17637
S.E. of regression	5.651522	Akaike info criterion	6.527797
Sum squared resid	415.2161	Schwarz criterion	7.667790
Log likelihood	-103.5559	Hannan-Quinn criter.	6.939982
F-statistic	8.938233	Durbin-Watson stat	2.194758
Prob(F-statistic)	0.000090		

(Source: Author, 2026)

Table 4.6 presents the dynamic ARDL estimates of the relationship between renewable energy value chain dynamics and manufacturing value added in Kenya. The selected specification is ARDL (1, 4, 4, 4, 4, 2, 1), selected using the Akaike Information Criterion, with 40 observations covering the adjusted sample period 1985–2024. The model captures both contemporaneous and lagged effects of renewable energy installation, generation, consumption and transmission-distribution losses on manufacturing value added, together with gross capital formation and labour.

Renewable energy installation exhibits predominantly delayed effects on manufacturing value added. The contemporaneous coefficient is 4.362, with a t-statistic of 0.173 and a probability value of 0.866 and is therefore statistically insignificant at the 5% level. Since renewable energy installation is expressed in natural logarithmic form while manufacturing value added is measured in levels, a 1% increase in renewable energy installation in the current period is associated with an approximate Ksh 0.044 billion increase in manufacturing value added, holding other factors constant. However, the high probability value indicates insufficient evidence to conclude that contemporaneous changes in renewable energy installation systematically affect manufacturing value added. The value of renewable energy installation one year earlier has a coefficient of -16.399, with a t-statistic of -0.801 and a probability value of 0.438, indicating a negative but statistically insignificant relationship at the 5% level. A 1% increase in renewable energy installation one year earlier is associated with an estimated Ksh

0.164 billion reduction in current manufacturing value added, holding other factors constant. Nevertheless, the statistical evidence is insufficient to establish a systematic effect.

The coefficient of renewable energy installation two years earlier is also negative and statistically insignificant, with a coefficient of -14.551, a t-statistic of -0.842 and a probability value of 0.415. A 1% increase in renewable energy installation two years earlier is associated with an estimated Ksh 0.146 billion reduction in current manufacturing value added. However, the probability value exceeds 0.050, indicating insufficient evidence at the 5% level to establish a systematic effect. On the other hand, the value of renewable energy installation three years earlier is positive and statistically significant at the 5% level, with a coefficient of 44.405, a t-statistic of 2.326 and a probability value of 0.037. Thus, a 1% increase in renewable energy installation three years earlier is associated with approximately Ksh 0.444 billion higher manufacturing value added, ceteris paribus. The delayed positive effect is economically plausible because newly installed renewable energy capacity may require time to be commissioned, connected to the electricity network and effectively incorporated into productive activities. Manufacturing firms may also require time to adjust production technologies, machinery utilization and productive capacity before additional renewable energy infrastructure translates into higher output.

The coefficient of renewable energy installation four years earlier has a positive coefficient of 34.424, a t-statistic of 1.691 and a probability value of 0.115 and is therefore statistically insignificant at the 5% level. Thus, a 1% increase in renewable energy installation four years earlier is associated with an estimated Ksh 0.344 billion increase in manufacturing value added. However, the probability value indicates insufficient evidence to establish a systematic effect. Renewable energy installation does not exhibit statistically significant contemporaneous effects or effects one, two, or four years earlier on manufacturing value added; the statistically supported positive effect occurs three years earlier, suggesting that the contribution of renewable energy capacity to manufacturing performance may depend on the time required for infrastructure deployment, system integration and productive utilization.

Renewable energy generation also exhibits a differentiated dynamic relationship with manufacturing value added. The contemporaneous coefficient is 0.042, with a t-statistic of 0.006 and a probability value of 0.995 and is therefore statistically insignificant at the 5% level. Since renewable energy generation is expressed in natural logarithmic form while manufacturing value added is measured in levels, a 1% increase in current renewable energy

generation is associated with an estimated Ksh 0.0004 billion increase in manufacturing value added. The very small estimated magnitude and extremely high probability value indicate insufficient evidence of a systematic contemporaneous effect. Renewable energy generation one year earlier has a positive but statistically insignificant coefficient of 10.056, a t-statistic of 0.965 and a probability value of 0.352. A 1% increase in renewable energy generation one year earlier is associated with approximately Ksh 0.101 billion higher current manufacturing value added; however, the probability value exceeds 0.050, indicating insufficient statistical evidence to establish a systematic effect. Renewable energy generation two years earlier is positive and statistically significant at the 5% level, with a coefficient of 24.554, a t-statistic of 3.000 and a probability value of 0.010. Therefore, a 1% increase in renewable energy generation two years earlier is associated with approximately Ksh 0.246 billion higher manufacturing value added, holding other factors constant. The delayed positive relationship may indicate that manufacturing firms require time to absorb additional electricity generation through adjustments in production processes, machinery utilization and productive capacity. Renewable energy generation three years earlier has a negative coefficient of -15.854, a t-statistic of -1.960 and a probability value of 0.072 and is therefore statistically insignificant at the study's specified 5% level. A 1% increase in renewable energy generation three years earlier is associated with an estimated Ksh 0.159 billion reduction in current manufacturing value added; however, because the probability value exceeds 0.050, there is insufficient evidence to conclude that renewable energy generation systematically reduces manufacturing value added at this point.

Renewable energy generation four years earlier is negative and statistically significant, with a coefficient of -22.494, a t-statistic of -2.863 and a probability value of 0.013. Thus, a 1% increase in renewable energy generation four years earlier is associated with approximately Ksh 0.225 billion lower manufacturing value added, holding other factors constant. This delayed negative association should not be treated as evidence that renewable energy generation is inherently detrimental to manufacturing. Rather, it may indicate that increased generation alone does not guarantee sustained manufacturing gains where complementary productive capacity, technology, energy-use efficiency, or industrial demand do not adjust sufficiently. Hence, renewable energy generation has no statistically significant contemporaneous or one-year-earlier effect, a positive and statistically significant effect associated with generation two years earlier, a negative but statistically insignificant association associated with generation three years earlier and a negative and statistically

significant effect associated with generation four years earlier. The changing signs across the time structure demonstrate that the relationship between renewable electricity generation and manufacturing performance is dynamic and varies over time.

Renewable energy consumption exhibits a predominantly delayed positive relationship with manufacturing value added. The contemporaneous coefficient is 2.231, with a t-statistic of 1.651 and a probability value of 0.123, making it statistically insignificant at the 5% level. Because renewable energy consumption enters the model in levels, a one-MWh increase in current renewable energy consumption is associated with an estimated Ksh 2.231 billion increase in manufacturing value added, holding other factors constant. However, the probability value exceeds 0.050, indicating insufficient statistical evidence to establish a systematic contemporaneous effect. Renewable energy consumption one year earlier has a positive but statistically insignificant coefficient of 1.010, a t-statistic of 0.743 and a probability value of 0.471. A one-MWh increase in renewable energy consumption one year earlier is associated with approximately Ksh 1.010 billion higher current manufacturing value added; nevertheless, the probability value indicates insufficient evidence at the 5% level to establish a systematic effect. Renewable energy consumption two years earlier is negative and statistically insignificant, with a coefficient of -0.482, a t-statistic of -0.296 and a probability value of 0.772. A one-MWh increase in renewable energy consumption two years earlier is associated with approximately Ksh 0.482 billion lower current manufacturing value added; however, the high probability value indicates that this negative association is not statistically distinguishable from zero at the 5% level.

On the other hand, renewable energy consumption three years earlier is positive and statistically significant, with a coefficient of 6.517, a t-statistic of 4.277 and a probability value of 0.001. Thus, a one-MWh increase in renewable energy consumption three years earlier is associated with approximately Ksh 6.517 billion higher manufacturing value added, holding other factors constant. The significant delayed effect suggests that the productive benefits of renewable energy consumption may require time to materialize as manufacturing firms adjust production processes, reorganize energy use, improve machinery utilization and integrate renewable electricity into productive activities. Renewable energy consumption four years earlier is positive but statistically insignificant, with a coefficient of 1.725, a t-statistic of 1.397 and a probability value of 0.186. A one-MWh increase in renewable energy consumption four years earlier is associated with an estimated Ksh 1.725 billion increase in manufacturing value

added; however, the probability value indicates insufficient evidence at the 5% level to establish a systematic effect. Therefore, renewable energy consumption has a statistically significant positive relationship with manufacturing value added specifically when measured three years earlier, while the contemporaneous value and values one, two and four years earlier are statistically insignificant at the 5% level. The findings suggest that the productive benefits of renewable energy consumption may emerge after a period of technological, operational and productive adjustment.

Transmission-distribution losses exhibit predominantly negative relationships with manufacturing value added. The contemporaneous coefficient is -25.498, with a t-statistic of -1.851 and a probability value of 0.087 and is therefore statistically insignificant at the 5% level. Since transmission-distribution losses are expressed in natural logarithmic form while manufacturing value added is measured in levels, a 1% increase in current transmission-distribution losses is associated with an estimated Ksh 0.255 billion reduction in manufacturing value added. However, the probability value exceeds 0.050, indicating insufficient evidence to establish a systematic contemporaneous effect. Transmission-distribution losses one year earlier are also negative and statistically insignificant, with a coefficient of -14.477, a t-statistic of -0.874 and a probability value of 0.398. A 1% increase in transmission-distribution losses one year earlier is associated with approximately Ksh 0.145 billion lower manufacturing value added; nevertheless, the statistical evidence is insufficient at the 5% level to establish a systematic effect. Transmission-distribution losses two years earlier have a coefficient of -37.278, a t-statistic of -1.836 and a probability value of 0.089 and are therefore statistically insignificant at the 5% level. A 1% increase in losses two years earlier is associated with an estimated Ksh 0.373 billion reduction in current manufacturing value added. However, the probability value indicates insufficient evidence at the 5% level to conclude that this negative association represents a systematic effect.

Transmission-distribution losses three years earlier are similarly negative and statistically insignificant, with a coefficient of -33.062, a t-statistic of -1.932 and a probability value of 0.076. Therefore, a 1% increase in losses three years earlier is associated with approximately Ksh 0.331 billion lower manufacturing value added; however, because the probability value exceeds 0.050, there is insufficient evidence to establish a systematic negative effect at this point. On the other hand, transmission-distribution losses four years earlier are negative and statistically significant, with a coefficient of -48.318, a t-statistic of -2.951 and a probability

value of 0.011. Thus, a 1% increase in transmission-distribution losses four years earlier is associated with approximately Ksh 0.483 billion lower manufacturing value added, holding other factors constant. This negative relationship is economically plausible because transmission-distribution losses reduce the quantity of electricity effectively available to productive users relative to the electricity entering the network. Persistent electricity losses can reduce energy-use efficiency, increase the effective cost of electricity supply and constrain manufacturing activity. The significant effect associated with losses four years earlier suggests that the adverse implications of electricity-system inefficiencies may become more evident after prolonged exposure. Transmission-distribution losses have negative estimated coefficients across all reported periods, but statistical significance at the 5% level is established only for losses four years earlier. The earlier negative coefficients therefore indicate associations in the expected direction but do not provide sufficient statistical evidence of systematic effects at the 5% level.

Gross capital formation has positive and statistically significant effects in the current period and one year earlier. The contemporaneous coefficient is 0.042, with a t-statistic of 2.763 and a probability value of 0.016. Thus, a Ksh one-billion increase in gross capital formation is associated with approximately Ksh 0.042 billion higher manufacturing value added, holding other factors constant. The positive relationship is economically consistent with investment expanding productive capacity through machinery, equipment, infrastructure and other capital assets. Gross capital formation one year earlier is also positive and statistically significant, with a coefficient of 0.057, a t-statistic of 2.837 and a probability value of 0.014. A one-billion increase in gross capital formation one year earlier is associated with approximately Ksh 0.057 billion higher current manufacturing value added. This delayed positive effect may arise because investment requires time to be installed, operationalized and incorporated into production processes. Gross capital formation two years earlier is positive but statistically insignificant, with a coefficient of 0.024, a t-statistic of 1.269 and a probability value of 0.227. A Ksh one-billion increase in gross capital formation two years earlier is associated with approximately Ksh 0.024 billion higher manufacturing value added; however, the probability value indicates insufficient evidence at the 5% level to establish a systematic effect at this point. Gross capital formation contributes positively to manufacturing value added in the current period and one year earlier, with statistical significance established at the 5% level for both periods, while its association with manufacturing value added two years earlier is positive but statistically insignificant.

Labour exhibits contrasting contemporaneous and lagged effects. The contemporaneous coefficient is 0.020, with a t-statistic of 3.882 and a probability value of 0.002, making it statistically significant at the 5% level. A one-unit increase in labour in the current period is associated with approximately Ksh 0.020 billion higher manufacturing value added, holding other factors constant. This positive relationship is consistent with labour being a fundamental productive input in manufacturing, as additional labour can expand productive capacity and facilitate more effective utilization of capital and energy resources. Labour one year earlier is negative and statistically significant, with a coefficient of -0.032, a t-statistic of -6.232 and a probability value of 0.000. A one-unit increase in labour one year earlier is associated with approximately Ksh 0.032 billion lower current manufacturing value added. The contrasting signs may reflect short-run adjustment processes in labour utilization. Although additional labour may increase productive capacity in the current period, its subsequent effect may depend on labour productivity, training, restructuring, technology adoption and the ability of firms to absorb workers efficiently. The negative effect associated with labour one year earlier should therefore be treated as a dynamic short-run association rather than as evidence that labour is generally harmful to manufacturing performance.

The lagged dependent variable, manufacturing value added one year earlier, has a coefficient of 0.148, a t-statistic of 1.120 and a probability value of 0.283, making it statistically insignificant at the 5% level. The positive coefficient indicates that a one-unit increase in manufacturing value added in the preceding period is associated with an estimated Ksh 0.148 billion increase in current manufacturing value added, holding the other variables constant. However, the probability value indicates insufficient evidence at the 5% level to conclude that previous-year manufacturing value added has an independent systematic effect on current manufacturing value added within the estimated model.

The constant term is positive and statistically significant, with a coefficient of 11.639, a t-statistic of 2.975 and a probability value of 0.011. This represents the estimated baseline level of manufacturing value added when the explanatory variables and their relevant lags are equal to zero. Because such a condition is unlikely to represent a meaningful economic state in the Kenyan manufacturing sector, the substantive economic inference of the constant is limited.

The model exhibits strong explanatory power, with an R-squared of 0.947 and an adjusted R-squared of 0.841. The R-squared indicates that approximately 94.702% of the variation in manufacturing value added is explained by the variables included in the ARDL specification.

After accounting for the number of explanatory variables and degrees of freedom, the adjusted R-squared indicates that approximately 84.107% of the variation remains explained by the model.

The F-statistic is 8.938, with a probability value of 0.000, indicating that the explanatory variables are jointly statistically significant at the 5% level. Thus, the model as a whole provides statistically significant explanatory power for manufacturing value added.

The standard error of regression is 5.652, indicating the typical magnitude of the model's residual error in the units of manufacturing value added. The Akaike Information Criterion is 6.528, the Schwarz Information Criterion is 7.668 and the Hannan-Quinn Criterion is 6.940. These information criteria are primarily useful for model selection and comparison rather than substantive economic analysis. The reported ARDL specification was selected using the Akaike Information Criterion.

The D-W statistic is 2.195, which is close to the benchmark value of 2.000 and does not by itself indicate serious first-order serial correlation. Nevertheless, the D-W statistic is not a substitute for formal residual diagnostic tests. Conclusions concerning serial correlation should therefore be based primarily on the formal diagnostic tests conducted for the model.

The ARDL results demonstrate that renewable energy value chain dynamics have predominantly delayed and differentiated relationships with manufacturing value added rather than uniform contemporaneous effects. Renewable energy installation has no statistically significant immediate effect on manufacturing value added, but its effect becomes positive and statistically significant when installation is measured three years earlier, with a 1% increase in renewable energy installation three years earlier associated with approximately Ksh 0.444 billion higher manufacturing value added. Renewable energy generation similarly exhibits a dynamic relationship with manufacturing performance, with a positive and statistically significant effect associated with generation two years earlier and a negative and statistically significant effect associated with generation four years earlier. Renewable energy consumption records a statistically significant positive effect specifically when consumption is measured three years earlier, while transmission-distribution losses are negative across the reported periods, with statistical significance established for losses four years earlier. Gross capital formation contributes positively to manufacturing value added in the current period and one year earlier, while labour has a positive contemporaneous effect but a negative effect associated

with labour one year earlier. These findings indicate that the effect of renewable energy value chain on manufacturing performance depends not only on the expansion of renewable energy capacity, generation and consumption, but also on the timing of energy availability, productive adjustment, actual utilization and electricity-system efficiency. Renewable energy investments are therefore more likely to translate into sustained manufacturing gains when supported by effective transmission-distribution infrastructure, adequate productive capacity, capital investment and efficient utilization of labour and energy.

The strong R-squared and adjusted R-squared values, together with the statistically significant F-statistic, indicate that the model provides substantial explanatory power. The D-W statistic of 2.195 does not indicate serious first-order serial correlation based on this statistic alone, subject to confirmation by the formal residual diagnostic tests. The ARDL results therefore provide the basis for the subsequent bounds-testing and error-correction analysis, which distinguishes the short-run dynamics from the long-run equilibrium relationship among the variables.

4.5.1.2 F-Bounds Test-Renewable Energy Value Chain Dynamics and Manufacturing Sector

Table 4.7 F-Bounds Test, manufacturing

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	8.041483	10%	2.12	3.23
K	6	5%	2.45	3.61
		2.5%	2.75	3.99
		1%	3.15	4.43

(Source; Author, 2026)

The F-Bounds test in Table 4.7 was conducted to examine the existence of a long-run relationship between manufacturing output and the set of renewable energy variables, including consumption, installation, generation and transmission-distribution losses, alongside control variables such as gross capital formation and labour. The computed F-statistic is 8.041. Comparing this statistic to the critical values from Pesaran et al. (2001) for case 3, with unrestricted constant and no trend, shows that it exceeds the upper bounds at all standard significance levels: 10% (3.23), 5% (3.61), 2.5% (3.99) and 1% (4.43). Since the F-statistic is well above the upper critical bounds, the null hypothesis of no levels relationship is decisively rejected.

This result implies that there is a stable long-run equilibrium relationship linking manufacturing output to renewable energy value chain dynamics and the key production inputs. Changes in renewable energy consumption, installation, generation and transmission-distribution losses, as well as capital and labour, are not merely transitory shocks; they have persistent effects that influence the level of manufacturing output over time. This aligns with endogenous growth and production function models, where energy and capital inputs are essential determinants of sectoral performance and the sector cannot operate in isolation from energy supply conditions. Rejecting the null validates the subsequent use of the ARDL-ECM framework, ensuring that both short-run adjustments and long-run equilibrium effects can be meaningfully estimated for the manufacturing sector.

4.5.1.3 ECM Analysis-Renewable Energy Value Chain Dynamics and Manufacturing Sector

Table 4.8 ECM Analysis, Manufacturing

Selected Model: ARDL(1, 4, 4, 4, 4, 2, 1)
Case 3: Unrestricted Constant and No Trend
Date: 03/17/26 Time: 15:19
Sample: 1981 2024
Included observations: 40

ECM Regression
Case 3: Unrestricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	11.63913	1.497566	7.772031	0.0000
D(REC)	2.230854	0.857900	2.600368	0.0220
D(REC(-1))	-7.759921	1.358411	-5.712498	0.0001
D(REC(-2))	-8.241760	1.054765	-7.813837	0.0000
D(REC(-3))	-1.724612	0.840113	-2.052833	0.0608
D(LNRET)	4.362119	14.85714	0.293604	0.7737
D(LNRET(-1))	-64.27866	19.71612	-3.260208	0.0062
D(LNRET(-2))	-78.82941	20.23093	-3.896480	0.0018
D(LNRET(-3))	-34.42419	12.70211	-2.710117	0.0178
D(LNREG)	0.041944	4.787313	0.008762	0.9931
D(LNREG(-1))	13.79404	8.680517	1.589081	0.1361
D(LNREG(-2))	38.34822	8.740261	4.387538	0.0007
D(LNREG(-3))	22.49441	5.861046	3.837952	0.0021
D(LNRNTL)	-25.49819	9.445189	-2.699595	0.0182
D(LNRNTL(-1))	118.6584	16.22670	7.312540	0.0000
D(LNRNTL(-2))	81.38037	14.12540	5.761278	0.0001
D(LNRNTL(-3))	48.31841	9.937413	4.862272	0.0003
D(GCF)	0.041879	0.008525	4.912483	0.0003
D(GCF(-1))	-0.024138	0.011655	-2.071039	0.0588
D(L)	0.020166	0.003973	5.075434	0.0002
CointEq(-1)*	-0.852269	0.093963	-9.070312	0.0000

R-squared	0.969136	Mean dependent var	0.329826
Adjusted R-squared	0.936648	S.D. dependent var	18.57292

S.E. of regression	4.674770	Akaike info criterion	6.227797
Sum squared resid	415.2161	Schwarz criterion	7.114458
Log likelihood	-103.5559	Hannan-Quinn criter.	6.548386
F-statistic	29.83041	Durbin-Watson stat	2.194758
Prob(F-statistic)	0.000000		

* p-value incompatible with t-Bounds distribution.
(Source; Author, 2026)

Table 4.8 presents the ECM model estimates of the short-run relationship between renewable energy value chain dynamics and manufacturing value added in Kenya. The error correction model is derived from the selected autoregressive distributed lag (1, 4, 4, 4, 4, 2, 1) specification and captures both short-run changes in the explanatory variables and the speed at which deviations from the long-run equilibrium relationship are corrected. The model includes changes in renewable energy consumption, renewable energy installation, renewable energy generation, transmission-distribution losses, gross capital formation and labour. The estimated error correction model therefore provides evidence on how temporary changes in these variables affect manufacturing value added during the adjustment process.

Renewable energy installation exhibits differentiated short-run effects across the adjustment period. The contemporaneous change in renewable energy installation has a coefficient of 4.362, a t-statistic of 0.294 and a probability value of 0.774 and is therefore statistically insignificant at the 5% level. Since renewable energy installation is expressed in natural logarithmic form while manufacturing value added is measured in levels, the coefficient indicates that a 1% increase in renewable energy installation in the current period is associated with an estimated Ksh 0.044 billion increase in manufacturing value added, holding other factors constant. However, the insignificant result means that there is insufficient statistical evidence at the 5% level to conclude that a current change in renewable energy installation systematically affects manufacturing value added in the short run. The change in renewable energy installation one year earlier has a coefficient of -64.279, a t-statistic of -3.260 and a probability value of 0.006, indicating a statistically significant negative effect at the 5% level. Hence, a 1% increase in renewable energy installation one year earlier is associated with approximately Ksh 0.643 billion lower current manufacturing value added, holding other factors constant. The negative short-run association may reflect the adjustment period required for newly installed renewable energy capacity to be commissioned, connected to the grid and integrated into productive activities.

The change in renewable energy installation two years earlier is also negative and statistically significant, with a coefficient of -78.829, a t-statistic of -3.896 and a probability value of 0.002. A 1% increase in renewable energy installation two years earlier is associated with approximately Ksh 0.788 billion lower current manufacturing value added. The statistically significant negative association suggests that the adjustment effects associated with renewable energy installation may persist into the second year. The change in renewable energy installation three years earlier remains negative and statistically significant, with a coefficient of -34.424, a t-statistic of -2.710 and a probability value of 0.018. Thus, a 1% increase in renewable energy installation three years earlier is associated with approximately Ksh 0.344 billion lower current manufacturing value added, holding other factors constant. Renewable energy installation has no statistically significant contemporaneous short-run effect, but its changes one, two and three years earlier have statistically significant negative associations with manufacturing value added. These results should be treated as short-run adjustment effects and not as evidence of a long-run negative effect of renewable energy installation. The negative effects associated with earlier periods may reflect the time required for infrastructure investments to become fully operational and productive.

Renewable energy generation also exhibits delayed short-run effects. The contemporaneous change in renewable energy generation has a coefficient of 0.042, a t-statistic of 0.009 and a probability value of 0.993 and is therefore statistically insignificant at the 5% level. Since renewable energy generation is expressed in logarithmic form, a 1% increase in current renewable energy generation is associated with an estimated Ksh 0.0004 billion increase in manufacturing value added. However, the very high probability value indicates insufficient evidence to conclude that current changes in renewable energy generation systematically affect manufacturing value added in the short run. The change in renewable energy generation one year earlier has a positive coefficient of 13.794, a t-statistic of 1.589 and a probability value of 0.136, making it statistically insignificant at the 5% level. A 1% increase in renewable energy generation one year earlier is associated with approximately Ksh 0.138 billion higher current manufacturing value added; nevertheless, because the probability value exceeds 0.050, there is insufficient statistical evidence to establish this as a systematic short-run effect.

The change in renewable energy generation two years earlier is positive and statistically significant, with a coefficient of 38.348, a t-statistic of 4.388 and a probability value of 0.001. A 1% increase in renewable energy generation two years earlier is associated with

approximately Ksh 0.383 billion higher current manufacturing value added, holding other factors constant. The delayed positive effect may indicate that manufacturing firms require time to adjust production processes, machinery utilization and energy-intensive activities before additional renewable electricity generation translates into higher output. The change in renewable energy generation three years earlier is also positive and statistically significant, with a coefficient of 22.494, a t-statistic of 3.838 and a probability value of 0.002. Thus, a 1% increase in renewable energy generation three years earlier is associated with approximately Ksh 0.225 billion higher manufacturing value added. The persistence of positive effects associated with generation two and three years earlier suggests that the productive contribution of renewable electricity generation may materialize gradually as firms adjust their production and energy-use patterns. Renewable energy generation has statistically insignificant contemporaneous effects and effects associated with generation one year earlier, but statistically significant positive effects associated with generation two and three years earlier. The insignificant coefficients indicate that the estimated short-run associations in the current period and one year earlier cannot be regarded as statistically established effects at the 5% level.

Renewable energy consumption exhibits contrasting short-run effects across the adjustment period. The contemporaneous change in renewable energy consumption has a coefficient of 2.231, a t-statistic of 2.600 and a probability value of 0.022, making it statistically significant at the 5% level. Since renewable energy consumption enters the model in levels and is measured in MWh, the coefficient is analyzed directly. Thus, a one-MWh increase in renewable energy consumption in the current period is associated with approximately Ksh 2.231 billion higher manufacturing value added, holding other factors constant. This positive relationship suggests that increased current utilization of renewable energy is associated with higher manufacturing output in the short run. The change in renewable energy consumption one year earlier is negative and statistically significant, with a coefficient of -7.760, a t-statistic of -5.712 and a probability value of 0.000. A one-MWh increase in renewable energy consumption one year earlier is associated with approximately Ksh 7.760 billion lower current manufacturing value added, holding other factors constant. The change in renewable energy consumption two years earlier is also negative and statistically significant, with a coefficient of -8.242, a t-statistic of -7.814 and a probability value of 0.000. Thus, a one-MWh increase in renewable energy consumption two years earlier is associated with approximately Ksh 8.242 billion lower current manufacturing value added.

The change in renewable energy consumption three years earlier has a coefficient of -1.725, a t-statistic of -2.053 and a probability value of 0.061 and is therefore statistically insignificant at the study's specified 5% level. A one-MWh increase in renewable energy consumption three years earlier is associated with approximately Ksh 1.725 billion lower manufacturing value added, but the probability value exceeds 0.050. Therefore, there is insufficient evidence at the 5% level to conclude that this negative association represents a systematic short-run effect. Renewable energy consumption has a statistically significant positive contemporaneous effect, followed by statistically significant negative effects associated with consumption one and two years earlier, while the effect associated with consumption three years earlier is negative but statistically insignificant at 5%. The changing signs indicate that the short-run relationship between renewable energy consumption and manufacturing value added is dynamic and may reflect adjustments in production processes, energy utilization and the allocation of other productive inputs.

Transmission-distribution losses exhibit a contrasting contemporaneous and earlier-period short-run relationship with manufacturing value added. The contemporaneous change in transmission-distribution losses has a coefficient of -25.498, a t-statistic of -2.700 and a probability value of 0.018, indicating a statistically significant negative effect at the 5% level. Therefore, a 1% increase in transmission-distribution losses in the current period is associated with approximately Ksh 0.255 billion lower manufacturing value added, holding other factors constant. This negative relationship is economically plausible because higher electricity losses reduce the amount of electricity effectively available to productive users and may increase the effective cost of electricity supply. The change in transmission-distribution losses one year earlier is positive and statistically significant, with a coefficient of 118.658, a t-statistic of 7.313 and a probability value of 0.000. A 1% increase in transmission-distribution losses one year earlier is associated with approximately Ksh 1.187 billion higher current manufacturing value added. The positive coefficient should not, however, be analyzed as indicating that electricity losses are beneficial to manufacturing. Rather, it reflects the estimated short-run dynamic association after controlling for the other variables in the model. The change in transmission-distribution losses two years earlier is also positive and statistically significant, with a coefficient of 81.380, a t-statistic of 5.761 and a probability value of 0.000. A 1% increase in transmission-distribution losses two years earlier is associated with approximately Ksh 0.814 billion higher current manufacturing value added.

The change in transmission-distribution losses three years earlier remains positive and statistically significant, with a coefficient of 48.318, a t-statistic of 4.862 and a probability value of 0.000. Thus, a 1% increase in transmission-distribution losses three years earlier is associated with approximately Ksh 0.483 billion higher current manufacturing value added. The significant negative contemporaneous effect is consistent with the economic costs of electricity-system inefficiency, while the positive effects associated with earlier periods represent statistical associations within the short-run adjustment process rather than evidence that increased electricity losses improve manufacturing performance. They may reflect adjustments in production schedules, energy sourcing, capacity utilization and other operational responses following earlier changes in electricity-system losses.

Gross capital formation has a positive and statistically significant contemporaneous short-run effect. The coefficient of the change in gross capital formation is 0.042, with a t-statistic of 4.912 and a probability value of 0.000. Since gross capital formation enters the model in levels and is measured in Ksh billions, a one-unit increase, equivalent to a Ksh one-billion increase in gross capital formation in the current period, is associated with approximately Ksh 0.042 billion higher manufacturing value added, holding other factors constant. The positive coefficient indicates a positive association between current capital formation and manufacturing value added. The change in gross capital formation one year earlier has a coefficient of -0.024, a t-statistic of -2.071 and a probability value of 0.059 and is therefore statistically insignificant at the 5% level. A one-unit increase in gross capital formation one year earlier is associated with approximately Ksh 0.024 billion lower current manufacturing value added. However, the probability value exceeds 0.050, indicating insufficient evidence to conclude that this negative association represents a systematic short-run effect. Thus, gross capital formation has a statistically significant positive contemporaneous effect, while its effect associated with the previous year is negative but statistically insignificant at the 5% level.

Labour has a positive and statistically significant contemporaneous effect on manufacturing value added. The coefficient of the change in labour is 0.020, with a t-statistic of 5.075 and a probability value of 0.000. Since one unit of labour represents 1,000 people, a one-unit increase in labour in the current period is associated with approximately Ksh 0.020 billion higher manufacturing value added, holding other factors constant. The positive relationship is consistent with the role of labour as a productive input in manufacturing, where additional labour can support production and facilitate the utilization of capital and energy resources. No

earlier-period change in labour appears in the selected error correction model specification. Therefore, the estimated short-run labour effect is confined to the contemporaneous period.

The error correction term has a coefficient of -0.852, a t-statistic of -9.070 and a probability value of 0.000, indicating a statistically significant negative coefficient at the 5% level. The negative and statistically significant coefficient indicates the presence of a systematic adjustment mechanism through which deviations from the long-run equilibrium are corrected. The error correction coefficient of -0.852 indicates that approximately 85.227% of the deviation from long-run equilibrium is corrected within one year. This represents a relatively rapid speed of adjustment. Thus, when short-run shocks cause manufacturing value added to deviate from its long-run equilibrium path, approximately 85.227% of the disequilibrium is corrected in the subsequent period, with the system moving relatively quickly back towards equilibrium. The results state that the probability value associated with the error correction term is incompatible with the t-Bounds distribution. Therefore, although the negative and statistically significant error correction coefficient provides evidence of a systematic adjustment mechanism, the existence of a long-run cointegrating relationship should be established primarily using the autoregressive distributed lag bounds test, rather than relying solely on the reported probability value of the error correction term.

The error correction model exhibits strong explanatory power, with an R-squared of 0.969 and an adjusted R-squared of 0.937. The R-squared indicates that approximately 96.914% of the variation in manufacturing value added is explained by the variables included in the error correction model. The adjusted R-squared indicates that approximately 93.665% of the variation remains explained after accounting for the number of explanatory variables and degrees of freedom.

The F-statistic is 29.830, with a probability value of 0.000, indicating that the explanatory variables are jointly statistically significant at the 5% level. Thus, the error correction model as a whole provides statistically significant explanatory power for manufacturing value added.

The standard error of regression is 4.675, indicating the typical magnitude of the model's residual error in the units of manufacturing value added. The Akaike Information Criterion is 6.228, the Schwarz Information Criterion is 7.114 and the Hannan-Quinn Criterion is 6.548.

These information criteria are primarily used for model comparison and assessment rather than substantive economic analysis.

The D-W statistic is 2.195, which is close to the benchmark value of 2.000. This does not provide a serious indication of first-order serial correlation. Nevertheless, the Durbin-Watson statistic is not a substitute for formal residual diagnostic tests; therefore, conclusions regarding serial correlation should primarily rely on the formal diagnostic tests reported subsequently.

The error correction model results demonstrate that renewable energy value chain dynamics have significant but differentiated short-run effects on manufacturing value added. The results reveal that the effects of renewable energy variables do not occur uniformly in the current period but vary across the adjustment period, with some effects emerging immediately and others becoming evident one or more years earlier. This pattern indicates that the short-run relationship between renewable energy value chain dynamics and manufacturing performance is shaped by the time required for infrastructure deployment, productive adjustment, energy utilization and operational responses. The negative and statistically significant error correction coefficient further indicates that deviations from the long-run equilibrium are corrected relatively rapidly, with approximately 85.227% of disequilibrium corrected within one year. However, because the probability value associated with the error correction term is incompatible with the t-Bounds distribution, the formal autoregressive distributed lag bounds test remains the appropriate basis for establishing the existence of a long-run cointegrating relationship. The error correction model provides evidence that manufacturing value added responds dynamically to changes in renewable energy value chain variables, capital formation and labour during the short-run adjustment process, while the subsequent bounds-testing results are required to establish the long-run relationship.

4.5.1.5 Diagnostic Tests-Renewable Energy Value Chain Dynamics and Manufacturing Sector

4.5.1.5.1 Renewable Energy Value Chain Dynamics and Manufacturing Sector, variance Inflation factors

Table 4.9 Variance Inflation Factors, Manufacturing

Variance Inflation Factors
Date: 03/17/26 Time: 15:20
Sample: 1981 2024
Included observations: 40

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
MVA(-1)	0.017384	9.104601	4.232656
REC	1.825464	5.286884	3.662551
REC(-1)	1.847551	5.348704	3.709920
REC(-2)	2.649517	7.707460	5.302335
REC(-3)	2.321446	6.722578	4.671197
REC(-4)	1.524118	4.383164	3.058708
LNRET	638.0647	8.030386	5.904905
LNRET(-1)	419.4723	5.279279	3.874819
LNRET(-2)	298.4420	3.750167	2.723866
LNRET(-3)	364.3491	3.572477	2.610791
LNRET(-4)	414.3604	4.264384	3.099631
LNREG	51.51651	3.190272	2.616349
LNREG(-1)	108.5061	6.703362	5.544470
LNREG(-2)	66.98721	4.227782	3.455111
LNREG(-3)	65.39933	4.114496	3.387093
LNREG(-4)	61.73923	3.986153	3.240675
LNRNTL	189.7271	3.116126	2.339868
LNRNTL(-1)	274.5987	4.540873	3.458129
LNRNTL(-2)	412.1547	6.755165	5.195701
LNRNTL(-3)	292.8967	4.885961	3.654255
LNRNTL(-4)	268.0068	4.579952	3.392226
GCF	0.000230	2.507155	2.092935
GCF(-1)	0.000399	4.250597	3.630272
GCF(-2)	0.000362	3.850793	3.289725
L	2.70E-05	11.88458	3.885560
L(-1)	2.59E-05	10.83217	3.770043
C	15.30238	19.16409	NA

(Source; Author, 2026)

The VIF results in Table 4.9 were computed to assess the extent of multicollinearity among the explanatory variables in the ARDL model for manufacturing output. Multicollinearity is a potential concern because high correlations among regressors can inflate standard errors, reduce the precision of coefficient estimates and distort inference. In this analysis, both uncentered and centered VIFs were reported, with the centered VIFs being more appropriate for analysis given the inclusion of lagged variables.

For the main renewable energy variables, renewable energy consumption and its lags exhibit centered VIFs ranging from 3.059 to 5.544, indicating moderate correlation among these lagged consumption terms but remaining below the conventional threshold of 10, suggesting that multicollinearity is not severe enough to undermine coefficient reliability. Similarly, renewable energy installation and its lags have centered VIFs between 2.611 and 5.905 and renewable energy generation ranges from 2.616 to 5.544, reflecting acceptable levels of multicollinearity that are common in time-series models with lagged explanatory variables. Transmission-distribution losses have centered VIFs between 2.340 and 5.196 showing

moderate correlation among lagged losses, which is expected given the persistence of transmission-distribution inefficiencies over time.

Among the controls, gross capital formation exhibits centered VIFs between 2.093 and 3.630, indicating minimal multicollinearity, while labour and its first lag have slightly higher VIFs of 3.770 to 3.886. Despite the relatively higher uncentered VIFs for labour and the constant term, the centered VIFs confirm that multicollinearity is not problematic for inference in the ARDL model. These findings suggest that the estimated effects of energy variables, gross capital formation and labour on manufacturing output can be analyzed with confidence and that the lagged structure necessary for capturing dynamic effects does not compromise the robustness of coefficient estimates. The moderate correlations among lagged variables reflect the persistence of energy use, installation, generation and losses over time, which is consistent with theoretical expectations for manufacturing production processes.

The VIF analysis reassures that the ARDL-ECM results for MVA are not distorted by severe multicollinearity and the reported coefficients provide reliable insights into the short-run and long-run influence of renewable energy and production inputs on manufacturing sector performance.

4.5.1.5.2 Renewable Energy Value Chain Dynamics and Manufacturing Sector, Test for Normality

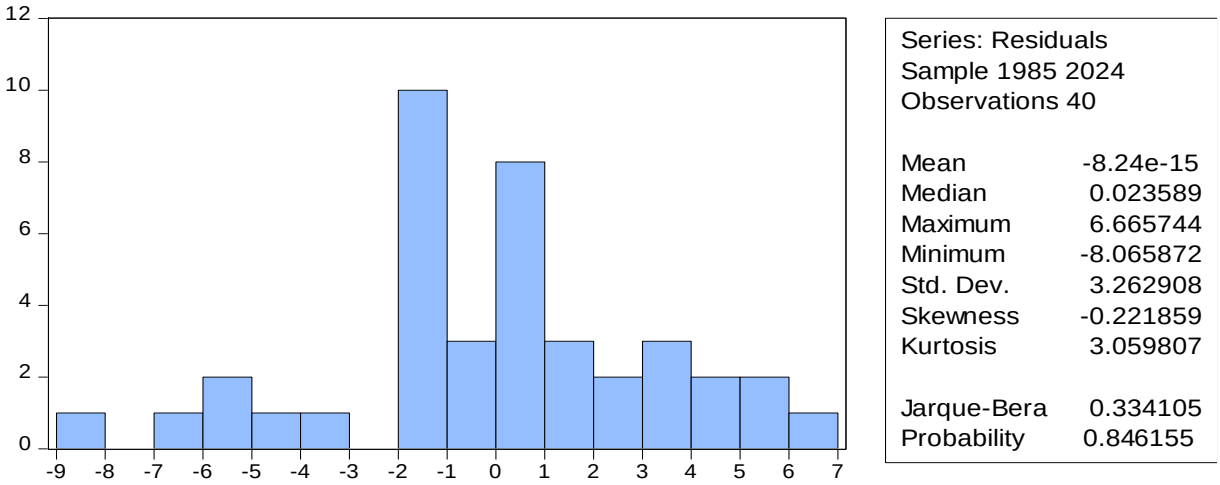


Figure 4.1 Normality Test, Manufacturing

(Source; Author, 2026)

The residuals of the manufacturing sector ECM model are approximately normally distributed as shown by Figure 4.1. The mean is effectively zero at -8.24e-15, the skewness is slightly negative, -0.222 and the kurtosis is close to 3, that is 3.060, indicating a roughly symmetric,

mesokurtic distribution. The J-B statistic of 0.334 with a p-value of 0.846 fails to reject the null hypothesis of normality, confirming that the residuals do not deviate significantly from a normal distribution. This suggests the model's assumptions for inference are valid.

4.5.1.5.3 Renewable Energy Value Chain Dynamics and Manufacturing Sector, Test for serial Correlation

Table 4.10 Test for Serial Correlation, Breusch-Godfrey Serial Correlation LM Test, Manufacturing

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.796850	Prob. F(3,10)	0.5232
Obs*R-squared	7.717337	Prob. Chi-Square(3)	0.0522

(Source; Author, 2026)

The Breusch-Godfrey Serial Correlation LM test in Table 4.10 was conducted to assess whether the residuals of the regression model exhibit serial correlation, which could compromise the efficiency of the OLS estimates. The test produced an F-statistic of 0.797 with a corresponding p-value of 0.523, indicating that the null hypothesis of no serial correlation cannot be rejected based on the F-test. Similarly, the Observed R-squared statistic was 7.717 with a p-value of 0.052, suggesting marginal evidence of serial correlation at the 5% significance level but remaining statistically insignificant at the conventional 5% threshold. These results collectively imply that there is no strong evidence of autocorrelation in the model residuals and therefore, the standard errors of the OLS estimates are reliable for inference. This finding reinforces the robustness of the regression results, ensuring that the relationships estimated between the explanatory and dependent variables are not distorted by serial dependence in the residuals.

4.5.1.5.4 Renewable Energy Value Chain Dynamics and Manufacturing Sector, Test for Heteroskedasticity

Table 4.11 Heteroskedasticity Test: Breusch-Pagan-Godfrey, Manufacturing

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	2.577207	Prob. F(26,13)	0.0385
Obs*R-squared	33.50060	Prob. Chi-Square(26)	0.1481
Scaled explained SS	3.644313	Prob. Chi-Square(26)	1.0000

(Source; Author, 2026)

The Breusch-Pagan-Godfrey test in Table 4.11 was employed to examine whether the variance of the regression residuals is constant, a key assumption of the classical linear regression model. The F-statistic was 2.577 with a corresponding p-value of 0.039, indicating statistical

significance at the 5% level and suggesting potential heteroskedasticity based on the F-test. On the other hand, the Observed R-squared statistic was 33.501 with a p-value of 0.148 and the Scaled explained sum of squares was 3.644 with a p-value of 1.000, both of which are statistically insignificant and do not provide evidence of heteroskedasticity. These mixed results indicate that there is no consistent evidence of heteroskedasticity in the model residuals. Thus, the OLS estimates can be considered reliable, although caution may be warranted when analyzing the F-test result. The absence of strong heteroskedasticity ensures that the estimated coefficients and their standard errors are robust, supporting the validity of inferences about the influence of renewable energy variables on sectoral performance.

4.5.1.5.6 Renewable Energy Value Chain Dynamics and Manufacturing Sector, CUSUM Test

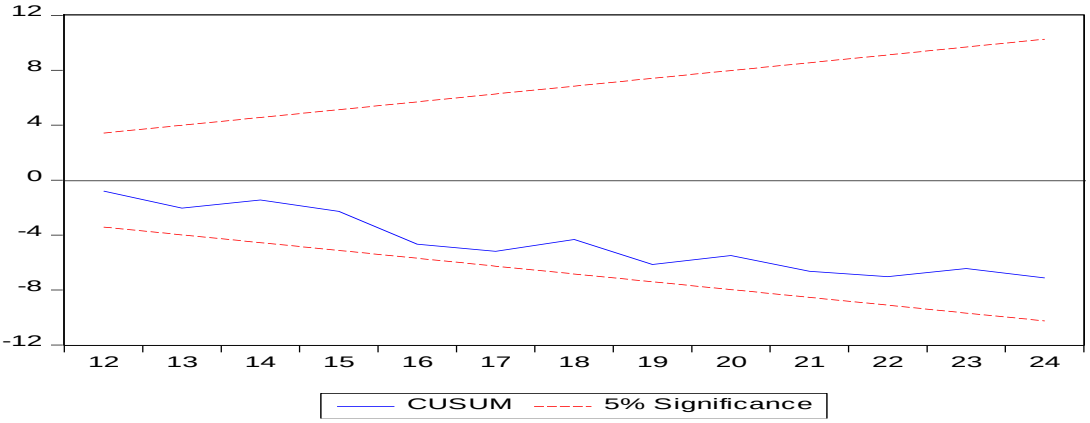


Figure 4.2 CUSUM Test, Manufacturing

(Source; Author, 2026)

The CUSUM test in Figure 4.2 was conducted to evaluate the stability of the regression coefficients over the sample period. In the plot, the blue line represents the cumulative sum of the recursive residuals, while the red dashed lines indicate the 5% significance bounds. The results show that the blue line remains entirely within the red critical boundaries throughout the sample period, indicating that there is no evidence of structural instability in the model coefficients. This implies that the relationships estimated between the explanatory variables and sectoral performance are stable over time and the model is reliable for forecasting and policy inference. The stability of coefficients further reinforces the robustness of the regression results, confirming that the estimated impacts of renewable energy variables on sectoral performance are consistent across the study period.

4.5.1.5.7 Renewable Energy Value Chain Dynamics and Manufacturing Sector, CUSUM Sum of Squares

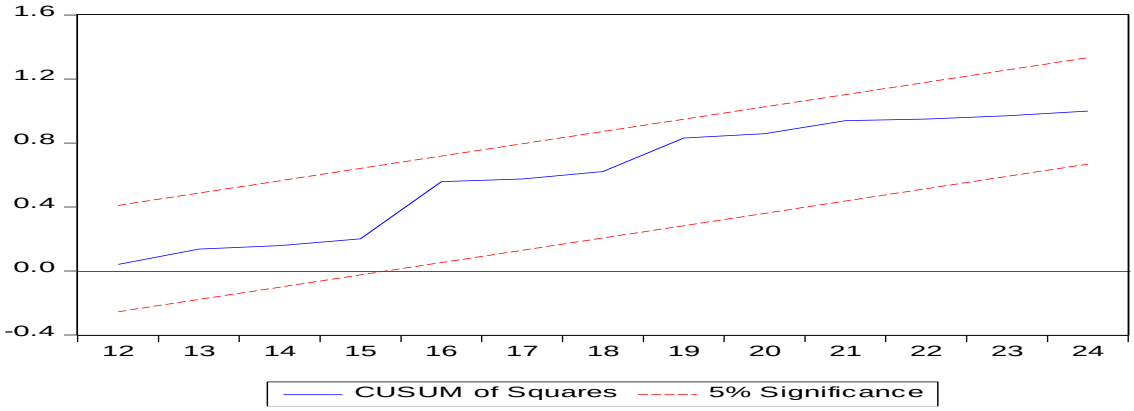


Figure 4.3 CUSUM Sum of Squares, Manufacturing
(Source; Author, 2026)

The stability of the estimated regression coefficients in Figure 4.3 was assessed using the CUSUM sum of squares test. The blue line represents the cumulative sum of the recursive residuals, while the red dashed lines indicate the 5% significance bounds. Throughout the sample period, the blue line remains entirely within the red critical boundaries, demonstrating that the coefficients do not exhibit structural instability. This finding implies that the relationships estimated between the explanatory variables, including renewable energy installation, generation, consumption and transmission losses and sectoral performance are stable over time. Thus, the regression model is robust, reliable for policy analysis and suitable for forecasting sectoral performance. The confirmed stability further reinforces the credibility of the estimated impacts, indicating that the effects of energy variables on manufacturing, agricultural and services outputs remain consistent across the entire study period.

4.5.2 Renewable Energy Value Chain Dynamics and Service Sector

4.5.2.1 Renewable Energy Value Chain Dynamics and Service Sector, ARDL Analysis

Table 4.12 ARDL Analysis, services

Dependent Variable: SVA
Method: ARDL
Date: 03/17/26 Time: 13:22
Sample (adjusted): 1985 2024
Included observations: 40 after adjustments
Maximum dependent lags: 3 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): LNRET LNREG REC LNRNTL
GCF L
Fixed regressors: C

Number of models evaluated: 46875
Selected Model: ARDL(3, 1, 3, 0, 3, 4, 1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
SVA(-1)	0.449292	0.160192	2.804717	0.0117
SVA(-2)	0.023767	0.177673	0.133766	0.8951
SVA(-3)	0.371419	0.158039	2.350166	0.0304
LNRET	396.8301	228.2119	1.738867	0.0991
LNRET(-1)	295.6636	239.9076	1.232406	0.2337
LNREG	-23.27558	76.85308	-0.302858	0.7655
LNREG(-1)	-204.3834	100.2186	-2.039375	0.0564
LNREG(-2)	-236.8641	81.33360	-2.912254	0.0093
LNREG(-3)	-206.8779	72.42356	-2.856500	0.0105
REC	60.26400	13.51247	4.459880	0.0003
LNRNTL	40.34914	144.4290	0.279370	0.7831
LNRNTL(-1)	-361.9625	186.6356	-1.939407	0.0683
LNRNTL(-2)	-344.6614	183.9680	-1.873486	0.0773
LNRNTL(-3)	-317.7502	210.6736	-1.508258	0.1488
GCF	-0.208665	0.183331	-1.138187	0.2700
GCF(-1)	-0.698958	0.207232	-3.372829	0.0034
GCF(-2)	0.122537	0.184232	0.665121	0.5144
GCF(-3)	-0.247815	0.166403	-1.489247	0.1537
GCF(-4)	0.371527	0.210429	1.765568	0.0944
L	0.239454	0.064684	3.701929	0.0016
L(-1)	-0.168991	0.061952	-2.727790	0.0138
C	58.66649	34.01710	1.724618	0.1017

R-squared	0.897366	Mean dependent var	154.9314
Adjusted R-squared	0.777627	S.D. dependent var	142.2567
S.E. of regression	67.08318	Akaike info criterion	11.55124
Sum squared resid	81002.77	Schwarz criterion	12.48012
Log likelihood	-209.0247	Hannan-Quinn criter.	11.88709
F-statistic	7.494341	Durbin-Watson stat	1.231907
Prob(F-statistic)	0.000034		

(Source; Author, 2026)

Table 4.12 presents the ARDL estimates of the dynamic relationship between renewable energy value chain variables and service-sector output in Kenya. The selected specification is ARDL (3, 1, 3, 0, 3, 4, 1), selected using the AIC. The model has an R-squared of 0.897, indicating that approximately 89.737% of the variation in service-sector output is explained by the variables included in the model. The adjusted R-squared is 0.778, indicating that approximately 77.763% of the variation is explained after accounting for the number of regressors and their lags. The F-statistic is 7.494, with a probability value of 0.000, indicating that the regressors are jointly statistically significant at the 5% level. The D-W statistic of 1.232 suggests some possibility of positive serial correlation; however, the D-W statistic alone is not sufficient to establish serial correlation and the formal serial-correlation diagnostic tests provide the appropriate basis for determining whether the model satisfies the relevant diagnostic condition.

The lagged dependent variable indicates persistence in service-sector output. The first lag of service-sector output has a positive coefficient of 0.449 and a probability value of 0.012, making it statistically significant at the 5% level. Thus, a Ksh 1 billion increase in service-sector output one year earlier is associated with an approximately Ksh 0.449 billion increase in current service-sector output, holding other factors constant. The second lag has a coefficient of 0.024 and a probability value of 0.895 and is therefore statistically insignificant at the 5% level. The third lag has a positive coefficient of 0.371 and a probability value of 0.030, making it statistically significant at the 5% level. Hence, a Ksh 1 billion increase in service-sector output three years earlier is associated with an approximately Ksh 0.371 billion increase in current service-sector output. The significant positive effects associated with service-sector output one and three years earlier indicate persistence in service-sector output, while the insignificant effect associated with service-sector output two years earlier indicates that the persistence is not uniform across all periods.

Renewable energy installation exhibits positive but statistically insignificant effects on service-sector output in the current period and one year earlier. The contemporaneous coefficient of renewable energy installation is 396.830, with a probability value of 0.099 and is therefore statistically insignificant at the specified 5% significance level. Because renewable energy installation is expressed in natural logarithmic form while service-sector output is measured in levels, this is a log-level relationship. Accordingly, a 1% increase in renewable energy installed capacity in the current period is associated with an approximately Ksh 3.968 billion increase in service-sector output, holding other factors constant. The effect associated with renewable energy installation one year earlier has a coefficient of 295.664 and a probability value of 0.234 and is likewise statistically insignificant at 5%. A 1% increase in renewable energy installed capacity one year earlier is associated with an approximately Ksh 2.957 billion increase in current service-sector output, ceteris paribus. Although both estimated coefficients are positive, their probability values exceed 0.050. Therefore, there is insufficient statistical evidence at the 5% level to establish a systematic relationship between renewable energy installation and service-sector output in the current period or one year earlier.

Renewable energy generation exhibits negative effects in the current period and across the reported earlier periods, with statistical significance established at two and three years earlier. The contemporaneous coefficient of renewable energy generation is -23.276, with a probability value of 0.766 and is statistically insignificant at the 5% level. Since renewable energy

generation is logarithmically transformed and service-sector output is measured in levels, a 1% increase in renewable energy generation in the current period is associated with an approximately Ksh 0.233 billion decrease in service-sector output. The effect associated with renewable energy generation one year earlier has a coefficient of -204.383 and a probability value of 0.056 and is also statistically insignificant at the specified 5% level. A 1% increase in renewable energy generation one year earlier is associated with an approximately Ksh 2.044 billion decrease in current service-sector output. The effect associated with renewable energy generation two years earlier has a coefficient of -236.864 and a probability value of 0.009, making it statistically significant at 5%. Thus, a 1% increase in renewable energy generation two years earlier is associated with an approximately Ksh 2.369 billion decrease in current service-sector output. The effect associated with renewable energy generation three years earlier is also negative and statistically significant, with a coefficient of -206.878 and a probability value of 0.011. Therefore, a 1% increase in renewable energy generation three years earlier is associated with an approximately Ksh 2.069 billion decrease in current service-sector output. Renewable energy generation has statistically insignificant effects in the current period and one year earlier, but statistically significant negative effects two and three years earlier.

Renewable energy consumption has a positive and statistically significant contemporaneous effect on service-sector output. The coefficient of renewable energy consumption is 60.264, with a probability value of 0.000, indicating statistical significance at the 5% level. Thus, a one-MWh increase in renewable energy consumption in the current period is associated with an approximately Ksh 60.264 billion increase in service-sector output, holding other factors constant. The statistically significant positive contemporaneous coefficient indicates that renewable energy consumption has a positive short-run association with service-sector output in the estimated ARDL model.

Transmission-distribution losses do not have statistically significant effects on service-sector output at the specified 5% significance level. The contemporaneous coefficient of transmission-distribution losses is 40.349, with a probability value of 0.783 and is therefore statistically insignificant. Because transmission-distribution losses are logarithmically transformed while service-sector output is measured in levels, a 1% increase in transmission-distribution losses in the current period is associated with an approximately Ksh 0.403 billion increase in service-sector output. The effect associated with transmission-distribution losses one year earlier has a coefficient of -361.963 and a probability value of 0.068. Therefore, a 1%

increase in transmission-distribution losses one year earlier is associated with an approximately Ksh 3.620 billion decrease in current service-sector output, but the effect is statistically insignificant at 5%. The effect associated with transmission-distribution losses two years earlier has a coefficient of -344.661 and a probability value of 0.077, implying that a 1% increase in transmission-distribution losses two years earlier is associated with an approximately Ksh 3.447 billion decrease in current service-sector output, also statistically insignificant at 5%. The effect associated with transmission-distribution losses three years earlier has a coefficient of -317.750 and a probability value of 0.149, indicating that a 1% increase in transmission-distribution losses three years earlier is associated with an approximately Ksh 3.178 billion decrease in current service-sector output, although the association is statistically insignificant. Thus, none of the estimated transmission-distribution loss coefficients is statistically significant at the 5% level and the results do not provide sufficient evidence to establish a systematic short-run relationship between transmission-distribution losses and service-sector output within this ARDL specification.

Gross capital formation exhibits mixed effects across the current period and earlier periods, with statistical significance established only for the effect associated with one year earlier. The contemporaneous coefficient of gross capital formation is -0.209, with a probability value of 0.270 and is therefore statistically insignificant. A billion increase in gross capital formation in the current period is associated with an approximately Ksh 0.209 billion decrease in current service-sector output, holding other factors constant, but the estimated association is not statistically supported at 5%. The effect associated with gross capital formation one year earlier has a coefficient of -0.699 and a probability value of 0.003, making it statistically significant at 5%. Thus, a Ksh 1 billion increase in gross capital formation one year earlier is associated with an approximately Ksh 0.699 billion decrease in current service-sector output, ceteris paribus. The effect associated with gross capital formation two years earlier has a positive coefficient of 0.123 and a probability value of 0.514 and is statistically insignificant, while the effect associated with gross capital formation three years earlier has a negative coefficient of -0.248 and a probability value of 0.154 and is also statistically insignificant. The effect associated with gross capital formation four years earlier has a positive coefficient of 0.372 and a probability value of 0.094 and is likewise statistically insignificant at the specified 5% level. Thus, gross capital formation has a statistically significant negative association with service-sector output one year earlier, while the contemporaneous effect and the effects associated with two, three and four years earlier are statistically insignificant at the 5% level.

Labour has statistically significant but contrasting contemporaneous and earlier-period effects on service-sector output. The contemporaneous coefficient of labour is 0.239, with a probability value of 0.002, indicating a statistically significant positive effect at the 5% level. A one-unit increase in labour in the current period is associated with an approximately Ksh 0.239 billion increase in service-sector output, holding other factors constant. The effect associated with labour one year earlier has a coefficient of -0.169 and a probability value of 0.014, making it statistically significant at 5%. Thus, a one-unit increase in labour one year earlier is associated with an approximately Ksh 0.169 billion decrease in current service-sector output, ceteris paribus. The results therefore indicate a positive contemporaneous association and a negative association with labour one year earlier.

The constant term has a coefficient of 58.666 and a probability value of 0.102, making it statistically insignificant at the 5% level. Therefore, there is insufficient statistical evidence to conclude that the intercept differs significantly from zero after controlling for the included variables and their lags. Its economic analysis is limited because it represents the predicted level of service-sector output when the explanatory variables and their relevant lagged values are equal to zero, which may not represent an economically meaningful situation.

The ARDL results demonstrate that the relationship between renewable energy value chain dynamics and service-sector output is characterized by substantial temporal variation. Renewable energy installation has positive but statistically insignificant associations in the current period and one year earlier, while renewable energy generation has statistically significant negative effects two and three years earlier. Renewable energy consumption has a positive and statistically significant contemporaneous association with service-sector output, whereas transmission-distribution losses do not exhibit statistically significant effects in the current period or any of the reported earlier periods. Gross capital formation has a statistically significant negative association one year earlier, while labour exhibits statistically significant positive and negative associations in the current period and one year earlier, respectively. These coefficients represent dynamic ARDL relationships and should not be regarded as long-run effects. The long-run relationship should instead be established from the estimated long-run coefficients, bounds test and corresponding error correction model.

The results show that renewable energy value chain variables do not affect service-sector output uniformly across time. Instead, the magnitude, direction and statistical significance of the estimated associations vary according to the specific component of renewable energy value chain dynamics and the period associated with each coefficient. The findings therefore indicate that the short-run relationship between renewable energy value chain dynamics and service-sector output differs across the components of the renewable energy value chain and across time. These short-run dynamics provide the basis for examining whether the observed relationships converge towards a stable long-run equilibrium through the subsequent bounds-testing and error correction analysis.

4.5.2.2 Renewable Energy Value Chain Dynamics and Service Sector, F-Bounds Test

Table 4.13 F-Bounds Test, Services

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	3.876318	10%	2.12	3.23
K	6	5%	2.45	3.61
		2.5%	2.75	3.99
		1%	3.15	4.43

(Source; Author, 2026)

The F-Bounds test presented in Table 4.13 was conducted to determine whether a long-run relationship exists between services sector output and its explanatory variables, namely renewable energy installation, renewable energy generation, renewable energy consumption, renewable energy transmission-distribution losses, gross capital formation and labour. The null hypothesis states that there is no levels relationship among the variables, while the alternative hypothesis indicates the existence of a long-run relationship. The computed F-statistic is 3.876, which is compared with the lower I (0) and upper I (1) critical bounds at different significance levels.

At the 10% significance level, the F-statistic of 3.876 exceeds both the lower bound of 2.12 and the upper bound of 3.23. Similarly, at the 5% significance level, the F-statistic exceeds the lower bound of 2.45 and the upper bound of 3.61. Therefore, the null hypothesis of no levels relationship is rejected at both the 10% and 5% significance levels, providing evidence of a long-run relationship between services sector output and the renewable energy, gross capital formation and labour variables. However, at the 2.5% significance level, the F-statistic lies between the lower bound of 2.75 and the upper bound of 3.99, while at the 1% significance

level it lies between the lower bound of 3.15 and the upper bound of 4.43. The results at these stricter significance levels are therefore inconclusive.

The evidence of a long-run relationship at the conventional 5% significance level suggests that services sector performance and the renewable energy value chain variables do not evolve independently over time. Rather, they share a stable long-run equilibrium relationship that also incorporates gross capital formation, labour and renewable energy transmission-distribution losses. This finding implies that changes in renewable energy infrastructure, energy availability and efficiency, capital accumulation and labour input can have persistent implications for services sector performance, even though their effects may differ in the short run.

The F-Bounds test provides sufficient evidence of a long-run relationship among the variables at the 5% significance level. This finding supports the use of the ARDL error correction framework to examine both the short-run dynamics and the speed at which deviations from the long-run equilibrium are corrected in the services sector.

4.5.2.3 Renewable Energy Value Chain Dynamics on Service Sector, ECM Analysis

Table 4.14 ECM Analysis, services

ARDL Error Correction Regression
Dependent Variable: D(SVA)
Selected Model: ARDL(3, 1, 3, 0, 3, 4, 1)
Case 3: Unrestricted Constant and No Trend
Date: 03/17/26 Time: 13:22
Sample: 1981 2024
Included observations: 40

ECM Regression
Case 3: Unrestricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	58.66649	12.31621	4.763356	0.0002
D(SVA(-1))	-0.395185	0.112853	-3.501777	0.0025
D(SVA(-2))	-0.371419	0.107516	-3.454536	0.0028
D(LNRET)	396.8301	157.8387	2.514150	0.0217
D(LNREG)	-23.27558	48.73453	-0.477599	0.6387
D(LNREG(-1))	443.7421	88.59977	5.008388	0.0001
D(LNREG(-2))	206.8779	57.13710	3.620729	0.0020
D(LNRNTL)	40.34914	100.5525	0.401274	0.6929
D(LNRNTL(-1))	662.4116	164.4699	4.027555	0.0008
D(LNRNTL(-2))	317.7502	136.1422	2.333959	0.0314
D(GCF)	-0.208665	0.131848	-1.582618	0.1309
D(GCF(-1))	-0.246249	0.135856	-1.812569	0.0866
D(GCF(-2))	-0.123712	0.133628	-0.925793	0.3668
D(GCF(-3))	-0.371527	0.116176	-3.197958	0.0050
D(L)	0.239454	0.043080	5.558396	0.0000
CointEq(-1)*	-0.155523	0.025856	-6.014895	0.0000

R-squared	0.878109	Mean dependent var	9.444350
Adjusted R-squared	0.801926	S.D. dependent var	130.5362
S.E. of regression	58.09574	Akaike info criterion	11.25124
Sum squared resid	81002.77	Schwarz criterion	11.92679
Log likelihood	-209.0247	Hannan-Quinn criter.	11.49549
F-statistic	11.52644	Durbin-Watson stat	1.231907
Prob(F-statistic)	0.000000		

* p-value incompatible with t-Bounds distribution.

(Source; Author, 2026)

Table 4.14 represents the ECM derived from the selected ARDL (3, 1, 3, 0, 3, 4, 1) specification and examines the short-run dynamics between renewable energy value chain variables and services-sector output in Kenya. The model is estimated using 40 observations and captures both short-run changes in services-sector output and the speed at which deviations from the estimated long-run equilibrium relationship are corrected. The model demonstrates strong explanatory power, with an R-squared of 0.878, indicating that approximately 87.811% of the variation in changes in services-sector output is explained by the variables included in the model. The adjusted R-squared of 0.802 indicates that approximately 80.193% of the variation remains explained after accounting for the number of regressors and degrees of freedom. The F-statistic is 11.526, with a probability value of 0.000, indicating that the explanatory variables are jointly statistically significant at the 5% level. The standard error of regression is 58.096, indicating the typical magnitude of the model's residual error in the units of services-sector output. The D-W statistic of 1.232 suggests the possibility of positive serial correlation; however, this statistic alone is insufficient to establish the presence of serial correlation and the formal diagnostic tests provide the appropriate basis for assessing this condition.

The constant term, C, is positive and statistically significant, with a coefficient of 58.666, a t-statistic of 4.763 and a probability value of 0.000. Because the dependent variable in the ECM is the change in services-sector output, the constant represents the estimated baseline change in SER after accounting for the short-run changes in the explanatory variables, lagged changes in service sector output and the ECM included in the model. It captures the average component of the change in services-sector output that is not accounted for by the explicitly included dynamic terms, conditional on the specification of the ECM. The positive coefficient suggests that, after controlling for the renewable energy value chain variables, gross capital formation, labour, lagged changes in services-sector output and the disequilibrium correction mechanism, there is a positive underlying component in the annual change in services-sector output. Since service sector output is measured in Ksh billions, the coefficient of 58.666 implies a baseline

increase of approximately Ksh 58.666 billion in services-sector output, conditional on the other terms of the model being held at their reference values. However, the constant should not be treated as an autonomous increase that would necessarily occur when all economic variables are literally zero, because such a situation is not economically realistic. Rather, its significance indicates that the model contains a statistically significant baseline component of services-sector change that is not fully captured by the measured explanatory variables. This is particularly important in an ECM because the constant operates alongside the short-run dynamics and the error-correction term; thus, its assessment is conditional on the structure of the estimated model rather than representing an independent causal effect of a particular economic variable.

The log of renewable energy installation has a positive and statistically significant contemporaneous short-run effect on services-sector output. The coefficient of D(LNRET) is 396.830, with a t-statistic of 2.514 and a probability value of 0.022, indicating significance at the 5% level. Thus, a 1% increase in renewable energy installed capacity in the current period is associated with an approximately Ksh 3.968 billion increase in services-sector output, holding other factors constant. The positive and statistically significant contemporaneous relationship is economically plausible because increased renewable energy capacity can expand the electricity infrastructure available to electricity-dependent service activities, including financial services, information and communication, hospitality, retail and other commercial activities. The immediate significance suggests that, unlike effects that require several years to materialize, changes in installed renewable energy capacity may translate relatively quickly into service-sector activity through improved electricity availability and productive capacity.

The log of renewable energy generation has an insignificant contemporaneous effect but significant positive lagged effects. The contemporaneous coefficient of D(LNREG) is -23.276, with a t-statistic of -0.478 and a probability value of 0.639, indicating that the estimated contemporaneous association is statistically insignificant at the 5% level. In log-level terms, a 1% increase in renewable energy generation in the current period is associated with an estimated Ksh 0.233 billion decrease in services-sector output, but there is insufficient statistical evidence to conclude that this represents a systematic short-run effect. On the other hand, the first lag has a coefficient of 443.742, a t-statistic of 5.008 and a probability value of 0.000, indicating a statistically significant positive effect. A 1% increase in renewable energy

generation one year earlier is associated with approximately Ksh 4.437 billion higher current services-sector output. The second lag is also positive and statistically significant, with a coefficient of 206.878, a t-statistic of 3.621 and a probability value of 0.002. Thus, a 1% increase in renewable energy generation two years earlier is associated with approximately Ksh 2.069 billion higher current services-sector output. The stronger first-lag coefficient indicates that the largest estimated delayed response occurs after one year. The pattern is economically plausible because electricity generation may require time to translate into productive service-sector activity through adjustments in business operations, investment, technology utilization and electricity-dependent services. The contrast between the insignificant contemporaneous effect and significant positive lagged effects therefore suggests that the benefits associated with additional renewable electricity generation are realized with a temporal delay rather than immediately.

The log of transmission-distribution losses has an insignificant contemporaneous effect but statistically significant positive lagged associations with services-sector output. The coefficient of D(LNRNTL) is 40.349, with a t-statistic of 0.401 and a probability value of 0.693, indicating statistical insignificance at the 5% level. Since transmission-distribution losses is logarithmically transformed, a 1% increase in transmission-distribution losses in the current period is associated with an estimated Ksh 0.403 billion increase in services-sector output, but this association is not statistically supported. The first lag has a coefficient of 662.412, a t-statistic of 4.028 and a probability value of 0.001, indicating a statistically significant positive association. A 1% increase in transmission-distribution losses one year earlier is associated with approximately Ksh 6.624 billion higher current services-sector output. The second lag is also positive and statistically significant, with a coefficient of 317.750, a t-statistic of 2.334 and a probability value of 0.031, implying that a 1% increase in losses two years earlier is associated with approximately Ksh 3.178 billion higher current services-sector output. Although these positive lagged coefficients are statistically significant, they should not be regarded as evidence that higher electricity losses improve services-sector performance. Such an assessment would be economically implausible because transmission-distribution losses represent inefficiencies in the electricity supply system. Instead, the positive lagged associations may capture the dynamic interaction between electricity flows, electricity demand and economic activity. For example, periods of increased electricity utilization and economic expansion may simultaneously be associated with higher measured system losses. The

coefficients should therefore be understood as conditional statistical associations within the ECM rather than causal evidence that electricity losses are beneficial to the services sector.

Gross capital formation exhibits predominantly negative short-run associations, although most are statistically insignificant. The contemporaneous coefficient is -0.209, with a t-statistic of -1.583 and a probability value of 0.131, indicating that a one-billion increase in gross capital formation in the current period is associated with an estimated Ksh 0.209 billion decrease in services-sector output, but the relationship is not statistically established at 5%. The first lag has a coefficient of -0.246 and a probability value of 0.087, while the second lag has a coefficient of -0.124 and a probability value of 0.367; both are therefore statistically insignificant at the study's specified 5% level. The third lag, however, has a coefficient of -0.372, a t-statistic of -3.198 and a probability value of 0.005, indicating a statistically significant negative association. A one-billion increase in gross capital formation three years earlier is associated with approximately Ksh 0.372 billion lower current services-sector output, holding other factors constant. The significant negative third-lag relationship may reflect the timing and adjustment costs associated with capital investment, whereby investment expenditure and the reorganization or installation of capital may precede the realization of its productive benefits. This short-run result should not be treated as evidence that gross capital accumulation is detrimental to services-sector growth in the long run.

Labour has a positive and statistically significant contemporaneous effect on services-sector output. The coefficient of D(L) is 0.239, with a t-statistic of 5.558 and a probability value of 0.000. Since labour is measured in levels, a one-unit increase in labour in the current period is associated with approximately Ksh 0.239 billion higher services-sector output, holding other factors constant. This positive relationship is economically consistent with the role of labour as a fundamental productive input in service activities, many of which rely directly on human skills, knowledge and labour services. The finding suggests that changes in labour availability are translated relatively quickly into services-sector output within the short-run adjustment process.

The lagged changes in services-sector output are both negative and statistically significant. D (SVA (-1) has a coefficient of -0.395, a t-statistic of -3.502 and a probability value of 0.003, while D(SVA (-2) has a coefficient of -0.371, a t-statistic of -3.455 and a probability value of 0.003. Thus, previous changes in services-sector output are negatively associated with

subsequent changes in current output. These negative coefficients may indicate short-run reversal or moderation following unusually large changes in services-sector activity. They may also reflect cyclical adjustment, whereby periods of relatively strong expansion are followed by slower growth as firms adjust their operations and capacity utilization. These coefficients describe short-run dynamics and should not be treated as evidence that higher services-sector output is detrimental to long-run sectoral performance.

The error correction term, CointEq (-1), is -0.156, with a t-statistic of -6.015 and a probability value of 0.000, indicating a negative and statistically significant adjustment coefficient at the 5% level. The negative sign is economically important because it indicates that when services-sector output deviates from the estimated long-run equilibrium relationship following a short-run disturbance, the subsequent adjustment tends to move the system back towards that equilibrium path. The magnitude of -0.156 indicates that approximately 15.552% of the disequilibrium from the previous period is corrected within one year. This represents a relatively gradual speed of adjustment compared with a model in which a much larger proportion of disequilibrium is corrected within a single period. The result suggests that the services sector does not immediately eliminate deviations from its equilibrium path following shocks to renewable energy value chain variables, capital formation, labour or other included factors. Instead, adjustment occurs progressively over time as firms, consumers and other economic agents respond to changes in energy availability, production conditions, investment and labour utilization. The coefficient therefore implies a degree of persistence in short-run disturbances: after one year, approximately 84.448% of the previous disequilibrium remains to be corrected, with the adjustment continuing in subsequent periods. The negative sign is essential because a positive error-correction coefficient would imply divergence rather than convergence towards equilibrium. Thus, the estimated coefficient provides evidence of a stable adjustment mechanism within the estimated dynamic specification. However, because the output explicitly indicates that the p-value associated with the error correction term is incompatible with the Bounds distribution, the existence of a long-run cointegrating relationship should be established primarily from the ARDL bounds test rather than inferred solely from the significance of CointEq (-1).

The ECM results indicate that renewable energy value chain variables affect services-sector output through differentiated short-run adjustment channels. Renewable energy installation has a statistically significant positive contemporaneous association, while renewable energy

generation produces its strongest positive effects one and two years earlier. Transmission-distribution losses have statistically significant positive lagged associations, although these should be treated as dynamic statistical relationships rather than evidence that electricity losses improve services-sector performance. Gross capital formation has a significant negative effect only three years earlier, while labour has a significant positive contemporaneous effect. The significant negative lagged changes in services-sector output further indicate short-run adjustment in sectoral activity. The error correction coefficient of -0.156 demonstrates that approximately 15.552% of the previous period's disequilibrium is corrected annually, indicating gradual convergence towards the estimated equilibrium path. The long-run cointegrating relationship should, however, be established using the ARDL bounds test and analyzed alongside the long-run coefficients.

4.5.2.2 Renewable Energy Value Chain Dynamics and Service Sector, Diagnostic Tests

4.5.2.2.1 Variance Inflation Factors

Table 4.15 Variance Inflation Factors, Services

Variance Inflation Factors
Date: 03/17/26 Time: 13:23
Sample: 1981 2024
Included observations: 40

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
SVA(-1)	0.025661	9.086621	4.258699
SVA(-2)	0.031568	10.08321	4.901779
SVA(-3)	0.024976	7.246879	3.663179
LNRET	52080.69	4.652131	3.420806
LNRET(-1)	57555.64	5.141178	3.773458
LNREG	5906.397	2.596016	2.128998
LNREG(-1)	10043.78	4.403914	3.642556
LNREG(-2)	6615.155	2.963222	2.421663
LNREG(-3)	5245.173	2.342106	1.928044
REC	182.5869	3.753182	2.600061
LNRNTL	20859.75	2.431633	1.825889
LNRNTL(-1)	34832.86	4.088212	3.113403
LNRNTL(-2)	33844.22	3.936984	3.028111
LNRNTL(-3)	44383.37	5.254837	3.930141
GCF	0.033610	2.603322	2.173214
GCF(-1)	0.042945	3.243977	2.770557
GCF(-2)	0.033941	2.564095	2.190502
GCF(-3)	0.027690	2.091602	1.772760
GCF(-4)	0.044280	3.089817	2.675117
L	0.004184	13.07647	4.275237
L(-1)	0.003838	11.38356	3.961946
C	1157.163	10.28554	NA

(Source; Author, 2026)

The VIFs in Table 4.15 were computed to assess potential multicollinearity among the explanatory variables in the services sector ARDL model. The results indicate that all variables have centered VIFs well below the conventional threshold of 10, with the highest being the contemporaneous labour variable (L) at 4.275 and the highest lag of the dependent variable SVA (-2) at 4.902. This suggests that multicollinearity is not a serious concern and each regressor provides sufficiently distinct information for the model. The assessment reassures that the short-run and lagged coefficients for renewable energy installation, generation, consumption, transmission losses, gross capital formation and labour are statistically reliable and can be analyzed without the distortions that high multicollinearity would otherwise introduce.

Including this VIF analysis supports the robustness of the elasticity-style log-level assessments, confirming that the observed relationships are not artifacts of overlapping explanatory power among the variables.

4.5.2.2.2 Test for Normality

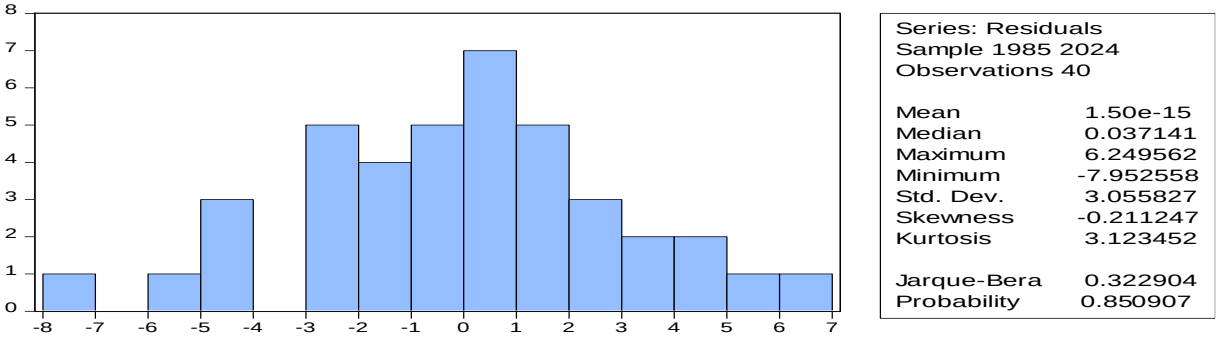


Figure 4.4 Normality Test, Services

(Source; Author, 2026)

The residuals of the manufacturing sector ECM model in Figure 4.4 are roughly normally distributed, with a nearly zero mean, slight negative skewness and a mesokurtic shape. The J-B test fails to reject normality, indicating that the residuals do not significantly deviate from a normal distribution and supporting the validity of the model's inferential assumptions.

4.5.2.2.3 Serial Correlation Test

Table 4.16 Test for Serial Correlation, Breusch-Godfrey Serial Correlation LM Test, Services

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	2.052622	Prob. F(3,15)	0.1497
Obs*R-squared	11.64175	Prob. Chi-Square(3)	0.0087

(Source; Author, 2026)

The Breusch-Godfrey Serial Correlation LM Test in Table 4.16 was conducted to check for autocorrelation in the residuals of the services sector ARDL model. The F-statistic of 2.053 with a corresponding p-value of 0.150 suggests that the null hypothesis of no serial correlation cannot be rejected at the conventional 1%, 5% or 10% levels. However, the Observed R-squared statistic of 11.642 with a p-value of 0.009 indicates mild evidence of serial correlation when using the Chi-square test.

The F-test implies that the residuals are reasonably free of first-order serial correlation, supporting the reliability of the short-run dynamics estimated in the model. The slight discrepancy with the Chi-square p-value suggests careful inference, but it does not fundamentally undermine the log-level elasticity analysis, such as the effects of renewable energy installation, generation and transmission losses on services output. This ensures that the percentage-change impacts derived from the model are robust to minor serial correlation concerns.

4.5.2.2.3 Test for Heteroskedasticity

Table 4.17 Heteroskedasticity Test: Breusch-Pagan-Godfrey, Services

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	0.440851	Prob. F(21,18)	0.9630
Obs*R-squared	13.58561	Prob. Chi-Square(21)	0.8867
Scaled explained SS	5.746447	Prob. Chi-Square(21)	0.9996

(Source; Author, 2026)

The Breusch-Pagan-Godfrey heteroskedasticity test in Table 4.17 was conducted to assess whether the variance of the residuals in the services sector ARDL model is constant across observations. The F-statistic of 0.441 with a p-value of 0.963 indicates that we fail to reject the null hypothesis of homoskedasticity. Similarly, the observed R-squared statistic of 13.586 with a p-value of 0.887 and the scaled explained sum of squares of 5.747 with a p-value of 0.999 all confirm that there is no evidence of heteroskedasticity in the model.

This implies that the residuals have a constant variance, which strengthens the reliability of the estimated log-level elasticities for the services sector. The percentage-change effects of renewable energy installation, generation, consumption and transmission-distribution losses on services output are not distorted by heteroskedasticity, ensuring that both short-run and long-run inference remain robust and economically meaningful.

4.5.2.2.4 CUSUM Test

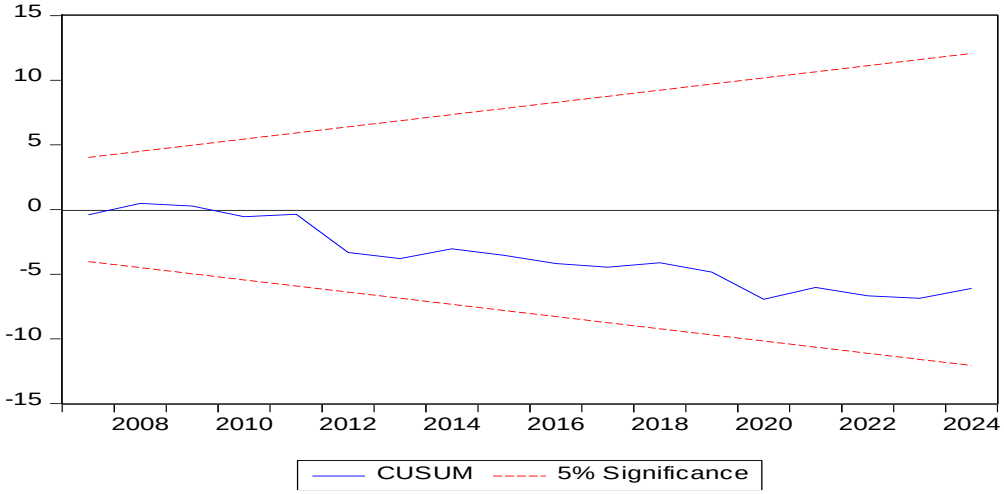


Figure 4.5 CUSUM Test, Services

(Source; Author, 2026)

The CUSUM test in Figure 4.5 shows that the regression coefficients are stable over time, as the cumulative residuals remain within the 5% significance bounds.

4.5.2.2.5 CUSUM Sum of Squares

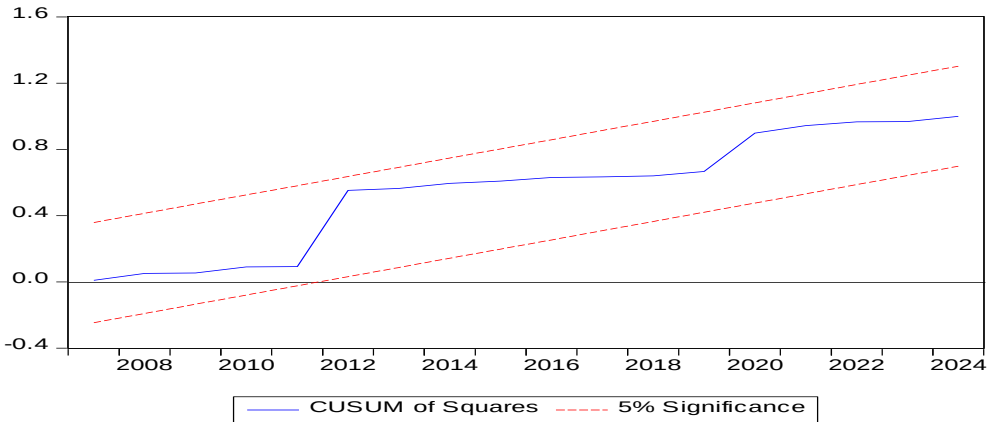


Figure 4.6 CUSUM Test, Services

(Source; Author, 2026)

The CUSUM of squares test in Figure 4.6 confirms that the variance of residuals is stable, with cumulative squared residuals staying within the critical limits, supporting the robustness of the model.

4.5.3 Renewable Energy Value Chain Dynamics and Agriculture Sector

4.5.3.1 Renewable Energy Value Chain Dynamics and Agriculture Sector, ARDL Analysis

Table 4.18 ARDL Analysis, Agriculture Sector

Dependent Variable: AVA

Method: ARDL
Date: 03/17/26 Time: 16:46
Sample (adjusted): 1984 2024
Included observations: 41 after adjustments
Maximum dependent lags: 1 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (3 lags, automatic): LNRET LNREG REC LNRNTL GCF L
Fixed regressors: C
Number of models evaluated: 4096
Selected Model: ARDL(1, 1, 3, 2, 1, 2, 1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
AVA(-1)	-0.074851	0.139492	-0.536596	0.5967
LNRET	-198.7383	78.87876	-2.519542	0.0191
LNRET(-1)	261.3896	79.23695	3.298834	0.0031
LNREG	-19.43358	32.07726	-0.605837	0.5506
LNREG(-1)	66.59858	38.87320	1.713226	0.1001
LNREG(-2)	-57.68580	36.37048	-1.586061	0.1264
LNREG(-3)	-61.90662	33.83351	-1.829743	0.0803
REC	-4.878260	5.764512	-0.846257	0.4061
REC(-1)	10.89871	5.254466	2.074180	0.0494
REC(-2)	-9.325488	6.547334	-1.424318	0.1678
LNRNTL	103.5752	60.94690	1.699433	0.1027
LNRNTL(-1)	135.2779	71.08643	1.903006	0.0696
GCF	0.249971	0.069959	3.573102	0.0016
GCF(-1)	0.064203	0.082936	0.774130	0.4467
GCF(-2)	-0.196324	0.078042	-2.515628	0.0193
L	0.017198	0.022140	0.776757	0.4452
L(-1)	0.026500	0.018583	1.426029	0.1673
C	-0.699315	12.71754	-0.054988	0.9566

R-squared	0.717267	Mean dependent var	28.78158
Adjusted R-squared	0.508290	S.D. dependent var	44.19242
S.E. of regression	30.98862	Akaike info criterion	10.00509
Sum squared resid	22086.78	Schwarz criterion	10.75739
Log likelihood	-187.1043	Hannan-Quinn criter.	10.27903
F-statistic	3.432280	Durbin-Watson stat	2.118768
Prob(F-statistic)	0.003314		

*Note: p-values and any subsequent tests do not account for model selection.

(Source; Author, 2026)

Table 4.18 presents the dynamic ARDL estimates for agricultural value added using the selected ARDL (1, 1, 3, 2, 1, 2, 1) specification. The model explains approximately 71.727% of the variation in agricultural value added, while the adjusted R-squared of 50.829% indicates that approximately 50.829% of the variation is explained after accounting for the number of regressors and their lags. The F-statistic of 3.432, with a probability value of 0.003, indicates that the regressors are jointly statistically significant at the 5% level. The D-W statistic of 2.119 does not indicate an obvious concern with positive first-order serial correlation; however, the D-W statistic alone is not sufficient for formal inference and the dedicated serial-correlation

diagnostic test should provide the basis for determining whether the model satisfies the relevant diagnostic condition.

The logarithm of renewable energy installation exhibits contrasting contemporaneous and lagged effects on agricultural value added. The contemporaneous coefficient of LNRET is -198.738, with a probability value of 0.019, indicating a statistically significant negative effect at the 5% level. Thus, a 1% increase in renewable energy installed capacity in the current period is associated with approximately Ksh 1.987 billion lower agricultural value added, holding other factors constant. The negative contemporaneous relationship may reflect short-run adjustment associated with the deployment, financing, connection and integration of new energy infrastructure, particularly where the productive benefits of newly installed capacity are not immediately realized. On the other hand, the first lag has a coefficient of 261.390 and a probability value of 0.003, indicating a statistically significant positive effect. A 1% increase in renewable energy installed capacity one year earlier is associated with approximately Ksh 2.614 billion higher current agricultural value added. The reversal from a significant negative contemporaneous association to a significant positive one-year lagged association suggests that the productive benefits of renewable energy installation may emerge after a period of adjustment, as agricultural producers gain access to and begin to utilize the additional energy infrastructure for activities such as irrigation, mechanization, processing and storage.

The logarithm of renewable energy generation does not exhibit a statistically significant effect on agricultural value added at the 5% level across the contemporaneous or lagged specifications. The contemporaneous coefficient is -19.434, with a probability value of 0.551, while the first lag has a coefficient of 66.599 and a probability value of 0.100. The second lag has a coefficient of -57.686, with a probability value of 0.126 and the third lag has a coefficient of -61.907, with a probability value of 0.080. Although the third lag provides weak evidence at the 10% level, it does not meet the study's specified 5% significance threshold. Therefore, there is insufficient statistical evidence to conclude that renewable energy generation has a systematic short-run effect on agricultural value added within the estimated specification. The alternating signs across the lags further indicate that generation alone does not produce a stable short-run relationship with agricultural output. This may reflect the distinction between electricity being generated and electricity being accessible and effectively utilized by agricultural producers. The productive contribution of renewable electricity generation may

depend on grid connectivity, affordability, reliability and the extent to which generated energy is converted into productive uses such as irrigation, mechanization, processing and storage.

Renewable energy consumption exhibits a delayed positive relationship with agricultural value added. The contemporaneous coefficient is -4.878, with a probability value of 0.406, indicating that the current-period association is statistically insignificant at the 5% level. The first lag, however, has a coefficient of 10.899 and a probability value of 0.049, indicating a statistically significant positive effect at the 5% level. Thus, a one-MW increase in renewable energy consumption one year earlier is associated with approximately Ksh 10.899 billion higher current agricultural value added, holding other factors constant. The second lag has a coefficient of -9.325 and a probability value of 0.168 and is therefore statistically insignificant. The pattern suggests that renewable energy consumption may contribute to agricultural output with a short delay rather than through an immediate response. This delayed effect is economically plausible because increased energy consumption may first need to be translated into productive agricultural activities, with output gains emerging after the completion of production cycles or through the gradual utilization of energy in irrigation, processing, storage and other value-adding activities.

The log of transmission-distribution losses has positive estimated coefficients in both the contemporaneous and first-lag specifications, although neither is statistically significant at the 5% level. The contemporaneous coefficient is 103.575, with a probability value of 0.103, while the first lag has a coefficient of 135.278 and a probability value of 0.070. The latter provides weak evidence at the 10% level but does not satisfy the study's specified 5% significance criterion. The first-lag coefficient implies that a 1% increase in transmission-distribution losses one year earlier is associated with approximately Ksh 1.353 billion higher current agricultural value added, holding other factors constant. However, because the coefficient is statistically insignificant at 5%, this association should not be seen as a statistically established effect. The positive sign should not be treated as evidence that higher electricity losses improve agricultural productivity. Rather, it may capture broader short-run interactions between electricity flows, energy demand and agricultural activity. For instance, periods of increased economic and electricity activity could coincide with higher measured system losses. The coefficient therefore represents an empirical association within the dynamic model and does not imply that increasing electricity losses would causally increase agricultural output.

Gross capital formation has contrasting contemporaneous and lagged effects on agricultural value added. The contemporaneous coefficient is 0.250, with a probability value of 0.002, indicating a statistically significant positive effect at the 5% level. A one-billion increase in gross capital formation in the current period is associated with approximately Ksh 0.250 billion higher agricultural value added, holding other factors constant. The first lag has a coefficient of 0.064 and a probability value of 0.447 and is therefore statistically insignificant. The second lag has a coefficient of -0.196 and a probability value of 0.019, indicating a statistically significant negative effect at the 5% level. Thus, a one-billion increase in gross capital formation two years earlier is associated with approximately Ksh 0.196 billion lower current agricultural value added. The contrasting signs suggest that the short-run relationship between capital formation and agricultural output varies according to the timing of investment. The contemporaneous positive effect is consistent with capital contributing directly to current productive capacity, whereas the delayed negative association may reflect adjustment costs, restructuring or temporary inefficiencies associated with the implementation and absorption of earlier investments. This short-run negative association is evidence that capital accumulation is detrimental to agricultural performance in the long run.

Labour does not have a statistically significant effect on agricultural value added in either the contemporaneous or first-lagged specification. The contemporaneous coefficient is 0.017, with a probability value of 0.445, while the first lag has a coefficient of 0.027 and a probability value of 0.167. Although both coefficients are positive, neither satisfies the 5% significance criterion. Therefore, there is insufficient statistical evidence to conclude that changes in labour have a systematic short-run effect on agricultural value added within the estimated specification. The lack of statistical significance may indicate that changes in labour quantity alone do not translate directly into measurable changes in agricultural output over the short adjustment period, particularly where productivity depends on complementary factors such as capital, technology, land, energy availability and climatic conditions.

The lagged dependent variable, AVA (-1), has a coefficient of -0.075, with a probability value of 0.597, indicating that the first lag of agricultural value added is statistically insignificant at the 5% level. The coefficient therefore provides insufficient evidence of systematic persistence in agricultural output through the lagged dependent variable within the estimated specification. The negative sign suggests a weak tendency towards short-run reversal, but because the

coefficient is statistically insignificant, this estimated direction should not be seen as an established dynamic effect.

The ARDL results indicate that the relationship between renewable energy value chain dynamics and agricultural value added is characterized by differentiated timing and statistical significance. Renewable energy installation has a statistically significant negative contemporaneous association followed by a statistically significant positive effect after one year, suggesting that the productive benefits of additional installed capacity may emerge after an initial adjustment period. Renewable energy consumption also has a statistically significant positive effect after one year, whereas renewable energy generation does not exhibit a statistically significant effect at the 5% level across its contemporaneous and lagged terms. Transmission-distribution losses have positive estimated coefficients, but neither the contemporaneous nor first-lagged effect is statistically significant at 5%; the first lag provides only weak evidence at the 10% level. Gross capital formation has a significant positive contemporaneous association and a significant negative association after two years, while labour remains statistically insignificant. The findings indicate that agricultural performance responds differently to the various components of renewable energy value chain dynamics and that the timing through which energy infrastructure, energy utilization and productive investment translate into agricultural output is important.

4.5.3.2 Renewable Energy Value Chain Dynamics and Agriculture Sector, F-Bounds Test

Table 4.19 F-Bounds Test, Agriculture

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	11.12433	10%	2.12	3.23
K	6	5%	2.45	3.61
		2.5%	2.75	3.99
		1%	3.15	4.43

(Source; Author, 2026)

The F-Bounds test in Table 4.19 was conducted to determine whether a long-run equilibrium relationship exists between agricultural output and the set of renewable energy variables alongside the control variables. The computed F-statistic is 11.12, which is substantially higher than all the upper bound critical values across conventional significance levels. Specifically, the upper bound values are 3.23 at 10%, 3.61 at 5%, 3.99 at 2.5% and 4.43 at 1%, all of which are well below the reported F-statistic.

This implies that the null hypothesis of no levels relationship is rejected even at the 1% significance level, providing strong evidence of cointegration among the variables. Agricultural output, renewable energy installation, generation, consumption, transmission-distribution losses, gross capital formation and labour move together in the long run.

This result confirms that the agricultural sector in Kenya is structurally linked to energy dynamics and key production inputs. Changes in renewable energy variables are not merely short-term fluctuations but have persistent effects on agricultural performance over time. Theoretically, this finding is consistent with production function and energy-growth nexus frameworks, which suggest that energy is a fundamental input in economic activity, including agriculture. The presence of cointegration therefore justifies the application of the ARDL-ECM approach, allowing for meaningful estimation of both long-run relationships and short-run adjustments in the agricultural sector model.

4.5.3.3 Renewable Energy Value Chain Dynamics and Agriculture Sector, ECM Analysis

Table 4.20 ECM Analysis, Agriculture

ARDL Error Correction Regression
Dependent Variable: D(AVA)
Selected Model: ARDL(1, 1, 3, 2, 1, 2, 1)
Case 3: Unrestricted Constant and No Trend
Date: 03/17/26 Time: 16:46
Sample: 1981 2024
Included observations: 41

ECM Regression
Case 3: Unrestricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.699315	4.328212	-0.161571	0.8731
D(LNRET)	-198.7383	45.20700	-4.396184	0.0002
D(LNREG)	-19.43358	22.25185	-0.873347	0.3915
D(LNREG(-1))	119.5924	31.93039	3.745411	0.0011
D(LNREG(-2))	61.90662	24.34246	2.543154	0.0182
D(REC)	-4.878260	4.073433	-1.197579	0.2433
D(REC(-1))	9.325488	3.768855	2.474355	0.0212
D(LNRNTL)	103.5752	37.45531	2.765300	0.0110
D(GCF)	0.249971	0.046117	5.420421	0.0000
D(GCF(-1))	0.196324	0.046725	4.201692	0.0003
D(L)	0.017198	0.014497	1.186322	0.2476
CointEq(-1)*	-1.074851	0.108474	-9.908801	0.0000

R-squared	0.874150	Mean dependent var	1.712225
Adjusted R-squared	0.826414	S.D. dependent var	66.23842
S.E. of regression	27.59734	Akaike info criterion	9.712405
Sum squared resid	22086.78	Schwarz criterion	10.21394
Log likelihood	-187.1043	Hannan-Quinn criter.	9.895036
F-statistic	18.31213	Durbin-Watson stat	2.118768

Prob(F-statistic)	0.000000

* p-value incompatible with t-Bounds distribution.
(Source; Author, 2026)

Table 4.20 presents the ECM for the short-run dynamics between renewable energy value chain variables and agricultural value added in Kenya. The ECM captures how short-run changes in renewable energy installation, generation, consumption, transmission-distribution losses, gross capital formation and labour are associated with changes in agricultural value added, while also indicating the speed at which deviations from the estimated long-run equilibrium relationship are corrected. The model has strong explanatory power, with an R-squared of 0.874, indicating that approximately 87.415% of the variation in changes in agricultural value added is explained by the variables included in the model. The adjusted R-squared of 0.826 indicates that approximately 82.600% of the variation is explained after accounting for the number of regressors and degrees of freedom. The F-statistic of 18.312, with a probability value of 0.000, indicates that the regressors are jointly statistically significant at the 5% level. The D-W statistic of 2.119 does not indicate serious positive first-order autocorrelation; however, formal inference on serial correlation should rely on the dedicated diagnostic test rather than the D-W statistic alone.

Renewable energy installation has a negative and statistically significant contemporaneous short-run effect on agricultural value added. The coefficient of D(LNRET) is -198.738, with a probability value of 0.000, indicating statistical significance at the 5% level. Thus, a 1% increase in renewable energy installed capacity in the current period is associated with an approximately Ksh 1.987 billion decrease in agricultural value added, holding other factors constant. This negative short-run association may reflect adjustment pressures associated with the deployment and integration of new renewable energy infrastructure. Such adjustment may involve land reallocation, changes in land use, disruption of existing agricultural activities or transitional costs before the infrastructure becomes fully operational. This suggests that renewable energy installation may impose short-run adjustment pressures on agricultural activity, even where its longer-term effects may differ.

Renewable energy generation has an insignificant contemporaneous effect but statistically significant positive effects one and two years earlier. The coefficient of the change in the logarithm of renewable energy generation is -19.434, with a probability value of 0.392, indicating a negative but statistically insignificant association at the 5% level, implying a 1% increase in renewable energy generation in the current period is associated with an estimated

Ksh 0.194 billion decrease in agricultural value added; however, there is insufficient statistical evidence to conclude that this effect differs from zero. The effect of renewable energy generation one year earlier has a coefficient of 119.592, with a probability value of 0.001, indicating a statistically significant positive effect at the 5% level, implying a 1% increase in renewable energy generation one year earlier is therefore associated with an approximately Ksh 1.196 billion increase in current agricultural value added. Similarly, the effect of renewable energy generation two years earlier has a coefficient of 61.907 and a probability value of 0.018, indicating a statistically significant positive effect at the 5% level. Thus, a 1% increase in renewable energy generation two years earlier is associated with an approximately Ksh 0.619 billion increase in current agricultural value added, holding other factors constant. These delayed positive effects suggest that the productive benefits of additional renewable electricity generation may require time to materialize as electricity becomes incorporated into irrigation, mechanization, agro-processing, refrigeration and storage activities.

Renewable energy consumption exhibits an insignificant contemporaneous effect but a statistically significant positive lagged effect. The coefficient of D(REC) is -4.878, with a probability value of 0.243, indicating a negative but statistically insignificant contemporaneous association at the 5% level. Thus, a one-MW increase in renewable energy consumption in the current period is associated with an estimated Ksh 4.878 billion decrease in agricultural value added; however, there is insufficient statistical evidence to conclude that this estimated effect differs from zero. On the other hand, D(REC(-1) has a coefficient of 9.325, with a probability value of 0.021, indicating a statistically significant positive effect at the 5% level. Since REC is measured in levels rather than logarithms, a one-MW increase in renewable energy consumption one year earlier is associated with an approximately Ksh 9.325 billion increase in current agricultural value added. The delayed response may reflect the time required for renewable energy consumption to translate into measurable improvements in agricultural production through irrigation, mechanization, drying, processing and storage.

Transmission-distribution losses have a positive and statistically significant contemporaneous association with agricultural value added. The coefficient of D(LNRNTL) is 103.575, with a probability value of 0.011, indicating significance at the 5% level, meaning a 1% increase in transmission-distribution losses in the current period is associated with an approximately Ksh 1.036 billion increase in agricultural value added, holding other factors constant. Although the positive sign may appear counterintuitive because higher electricity losses would ordinarily be expected to reduce the electricity effectively available for productive activities, the coefficient

represents the estimated statistical association within the model and should not be treated as evidence that energy losses improve agricultural productivity. The positive association may reflect the broader electricity system, including periods when increased electricity flows, demand and economic activity are accompanied by higher measured losses. The finding should therefore be treated cautiously and does not imply that reducing electricity losses would harm agricultural output.

Gross capital formation has positive and statistically significant short-run effects both contemporaneously and after one year. The coefficient of D(GCF) is 0.250, with a probability value of 0.000, indicating significance at the 5% level, meaning a one-billion increase in gross capital formation in the current period is associated with an approximately Ksh 0.250 billion increase in agricultural value added, holding other factors constant. The first lag, D(GCF (-1), has a coefficient of 0.196, with a probability value of 0.000, also indicating a statistically significant positive effect at the 5% level. Thus, a one-billion increase in gross capital formation one year earlier is associated with an approximately Ksh 0.196 billion increase in current agricultural value added. These results indicate that capital accumulation can support agricultural production through investment in machinery, irrigation infrastructure, farm equipment, storage facilities and other productive assets. The persistence of the positive effect after one year further suggests that capital investments continue to contribute to agricultural production beyond the period in which they are initially undertaken.

Labour has a positive but statistically insignificant contemporaneous effect on agricultural value added. The coefficient of D(L) is 0.017, with a probability value of 0.248, indicating that the estimated positive association is not statistically significant at the 5% level. A unit increase in labour is associated with an estimated Ksh 0.017 billion increase in agricultural value added, holding other factors constant. However, there is insufficient statistical evidence to conclude that changes in labour generate a measurable short-run change in agricultural value added within the estimated model. This may indicate that variations in labour alone are insufficient to generate substantial short-run changes in agricultural output once energy and capital inputs are accounted for.

The ECM term, CointEq (-1), is negative and highly statistically significant, with a coefficient of -1.075 and a probability value of 0.000. The negative sign indicates that deviations from the estimated long-run equilibrium relationship are followed by corrective movements in agricultural value added, while the statistical significance indicates that this adjustment

mechanism is systematically different from zero. The magnitude of the coefficient, approximately -1.075, implies that about 107.485% of the previous period's disequilibrium is corrected within one year. Because the absolute value of the coefficient exceeds one, the adjustment process involves overshooting. When agricultural value added deviates from its equilibrium path following a short-run disturbance, the subsequent adjustment is sufficiently strong to correct the entire previous disequilibrium and move beyond the equilibrium position. Subsequent adjustments can then bring the system back toward equilibrium. The result therefore indicates a very rapid but potentially oscillatory adjustment process rather than a gradual, monotonic return to equilibrium. This magnitude also suggests that the agricultural sector responds strongly to deviations from its equilibrium relationship, implying considerable short-run responsiveness in the adjustment process. Nevertheless, because the reported p-value of the ECT is incompatible with the t-Bounds distribution, the existence of a long-run cointegrating relationship should be established from the formal ARDL bounds test rather than inferred from the ECT alone.

The ECM results demonstrate that renewable energy value chain dynamics have differentiated short-run effects on agricultural value added. Renewable energy installation is associated with a significant contemporaneous decline, whereas renewable energy generation produces significant positive effects after one and two years, indicating that the productive contribution of renewable electricity may require time to materialize. Renewable energy consumption similarly exhibits a significant positive effect after one year, while transmission-distribution losses have a significant positive contemporaneous association. Gross capital formation contributes positively both contemporaneously and with a one-year lag, while labour does not exhibit a statistically significant short-run effect. The ECM coefficient of -1.075 indicates a 107.485% adjustment within one year, implying rapid convergence accompanied by overshooting. The findings indicate that agricultural output responds to renewable energy value chain dynamics through both immediate and delayed channels, while short-run disturbances generate a strong corrective response towards the estimated equilibrium path. The formal bounds test and long-run coefficient estimates remain the appropriate basis for establishing the long-run relationship.

4.5.3.4 Renewable Energy Value Chain Dynamics and Agriculture Sector, Diagnostic Tests

4.5.3.4.1 Renewable Energy Value Chain Dynamics and Agriculture Sector, Variance Inflation Factors

Table 4.21 Variance Inflation Factors, Agriculture

Variance Inflation Factors
Date: 03/17/26 Time: 16:48
Sample: 1981 2024
Included observations: 41

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
AVA(-1)	0.019458	2.135632	1.526885
LNRET	6221.859	2.604506	1.930277
LNRET(-1)	6278.494	2.628212	1.944368
LNREG	1028.951	2.119439	1.749291
LNREG(-1)	1511.126	3.180882	2.593065
LNREG(-2)	1322.812	2.776986	2.278899
LNREG(-3)	1144.707	2.467369	1.998582
REC	33.22959	3.204508	2.226686
REC(-1)	27.60941	2.675363	1.844121
REC(-2)	42.86758	4.150073	2.869954
LNRNTL	3714.524	2.044857	1.578808
LNRNTL(-1)	5053.281	2.783508	2.120625
GCF	0.004894	1.777646	1.496915
GCF(-1)	0.006878	2.436482	2.097214
GCF(-2)	0.006091	2.157688	1.844411
L	0.000490	7.180589	2.443902
L(-1)	0.000345	4.800995	1.728894
C	161.7359	6.905352	NA

(Source; Author, 2026)

The VIF results in Table 4.21 indicate that multicollinearity is not a serious concern in the agriculture sector ARDL model. The centered VIF values are generally low across all variables. The lagged dependent variable AVA (-1) has a centered VIF of 1.527, indicating a very weak correlation with other regressors. Renewable energy installation, represented by LNRET and its lag, records centered VIF values of 1.930 and 1.944, showing minimal multicollinearity.

Renewable energy generation variables also exhibit low to moderate correlation, with centered VIF values ranging from 1.750 for the contemporaneous term to 2.593 for the first lag, while the second and third lags remain below 2.300. Renewable energy consumption shows slightly higher but still acceptable levels, with centered VIF values of 2.227 for the current term, 1.844 for the first lag and 2.870 for the second lag. Transmission-distribution losses have centered VIF values of 1.579 and 2.121, indicating weak correlation among the loss variables.

Among the control variables, gross capital formation exhibits very low centered VIF values ranging from 1.500 to 2.097, confirming minimal multicollinearity. Labour shows a slightly higher centered VIF of 2.444 for the current term and 1.729 for its lag, but these values remain well below the conventional threshold of 10. Although some uncentered VIF values appear higher, particularly for labour and the constant term, these are not of primary concern in the presence of lagged variables.

All centered VIF values fall comfortably below the critical threshold, indicating that the explanatory variables are not excessively correlated. This suggests that renewable energy installation, generation, consumption, transmission losses, capital and labour capture distinct aspects of agricultural production dynamics. Therefore, the estimated coefficients from the ARDL-ECM models can be treated with confidence, as they are not distorted by severe multicollinearity.

4.5.3.4.2 Renewable Energy Value Chain Dynamics and Agriculture Sector, Test for Normality

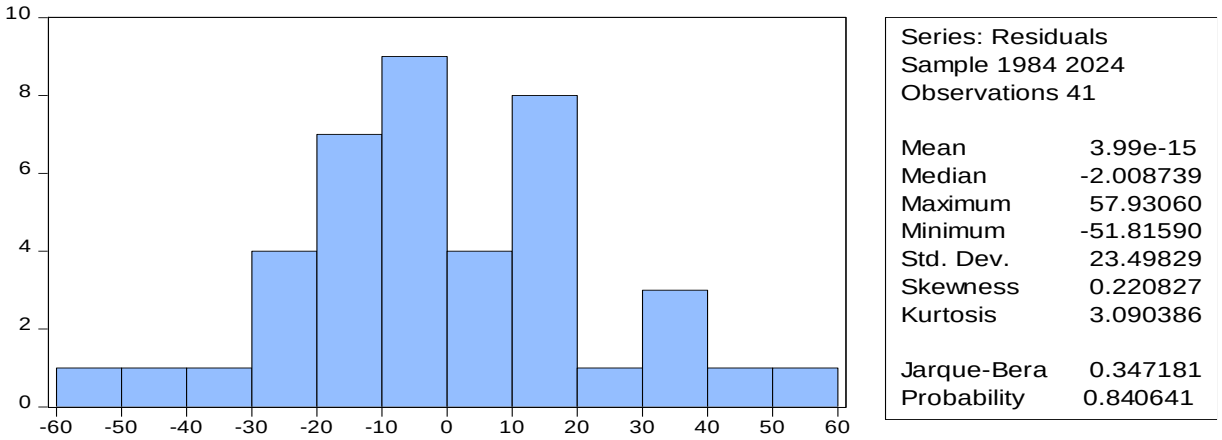


Figure 4.7 Normality Test, Agriculture

(Source; Author, 2026)

The residuals in Figure 4.7 from the agriculture sector model are approximately normally distributed. The mean is effectively zero at 3.99e-15, while the skewness of 0.221 indicates slight positive asymmetry. The kurtosis of 3.090 is close to the normal benchmark of 3, suggesting a near-normal distribution. The J-B statistic of 0.347 with a probability value of 0.841 fails to reject the null hypothesis of normality, confirming that the residuals do not significantly deviate from a normal distribution and that the model satisfies the normality assumption for reliable inference.

4.5.3.4.3 Renewable Energy Value Chain Dynamics and Agriculture Sector, serial Correlation Test

Table 4.22 Test for Serial Correlation, Breusch-Godfrey Serial Correlation LM Test:, Agriculture

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.242466	Prob. F(2,21)	0.7869
Obs*R-squared	0.925404	Prob. Chi-Square(2)	0.6296

(Source; Author, 2026)

The Breusch-Godfrey LM test in Table 4.22 indicates that there is no evidence of serial correlation in the model residuals. The F-statistic is 0.242 with a probability value of 0.787, while the Observed R-squared statistic is 0.925 with a probability value of 0.630. Since both probability values are well above conventional significance levels, the null hypothesis of no serial correlation cannot be rejected. This confirms that the residuals are independently distributed and that the model does not suffer from autocorrelation, ensuring the reliability of the estimated coefficients and statistical inferences.

4.5.3.4.4 Renewable Energy Value Chain Dynamics and Agriculture Sector, Test for Heteroskedasticity

Table 4.23 Heteroskedasticity Test: Breusch-Pagan-Godfrey, Agriculture

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	0.592465	Prob. F(17,23)	0.8642
Obs*R-squared	12.48637	Prob. Chi-Square(17)	0.7698
Scaled explained SS	4.106961	Prob. Chi-Square(17)	0.9994

(Source; Author, 2026)

The Breusch-Pagan-Godfrey test in Table 4.23 was employed to examine the presence of heteroskedasticity in the model, thereby assessing whether the variance of the regression residuals remained constant across observations. The F-statistic yielded a value of 0.592 with an associated probability of 0.864, indicating a lack of statistical significance. Similarly, the chi-square variant of the test, represented by Observed R-squared, produced a value of 12.486 with a corresponding p-value of 0.770, while the scaled explained sum of squares yielded 4.107 with a probability of 0.999. All three test outcomes consistently fail to reject the null hypothesis of homoskedasticity at conventional significance levels of 1%, 5% and 10%. This implies that the residuals of the model do not exhibit systematic variation with respect to the explanatory variables, thereby satisfying the assumption of constant variance. The absence of

heteroskedasticity enhances the reliability of the model's estimated standard errors and associated test statistics, confirming that inferences drawn from the regression coefficients is robust. This result suggests that the variability in sectoral performance or energy-related variables captured by the model does not disproportionately increase or decrease with the scale of the independent factors, indicating stable relationships across the dataset. The findings provide confidence that the regression model is correctly specified with respect to the homoskedasticity assumption and that subsequent treatment of coefficients can be undertaken without concern for bias in standard errors arising from heteroskedasticity.

4.5.3.4.5 Renewable Energy Value Chain Dynamics and Agriculture Sector, CUSUM Test

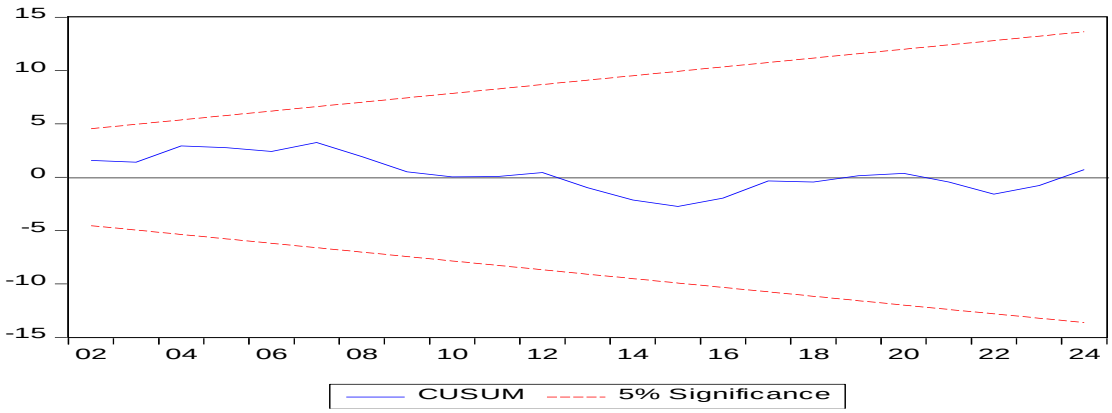


Figure 4.8 CUSUM Test, Agriculture

(Source; Author, 2026)

The CUSUM test in Figure 4.8 evaluates the stability of regression coefficients over time. In this analysis, the cumulative sum of recursive residuals remained entirely within the 5% significance bounds, indicating that there is no structural instability and that the model's relationships are consistent throughout the sample period.

4.5.3.4.6 Renewable Energy Value Chain Dynamics and Agriculture Sector, CUSUM Sum of Squares

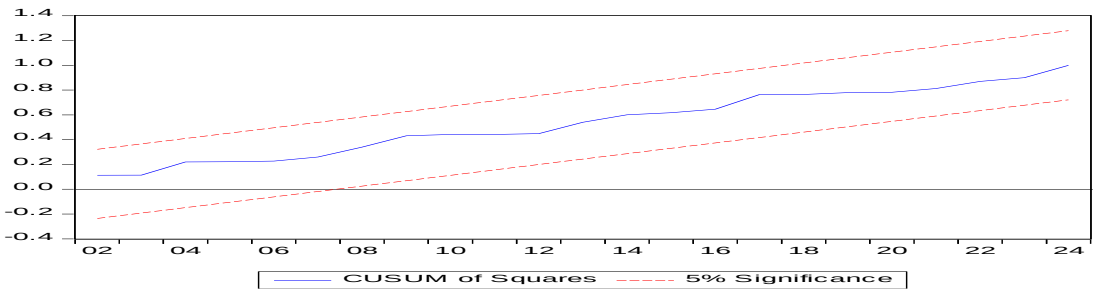


Figure 4.9 CUSUM Sum of Squares, Agriculture

(Source; Author, 2026)

The CUSUM of squares test in Figure 4.9 assesses changes in the variance of residuals. The plot shows that the cumulative squared residuals also stay within the critical boundaries, suggesting that the model's variance is stable and that the estimated effects of renewable energy variables on sectoral performance are reliable and robust.

4.6 Discussion of Results

4.6.1 Renewable Energy Value Chain Dynamics and the Manufacturing Sector

The findings of this study demonstrate that renewable energy value chain dynamics have heterogeneous and time-dependent implications for manufacturing performance in Kenya. The results indicate that the productive contribution of renewable energy cannot be understood simply in terms of whether renewable capacity or generation increases; rather, the economic benefits depend on the extent to which newly available energy is successfully integrated into industrial production and converted into productive use. This finding is consistent with the theoretical proposition that energy contributes to output as a productive input alongside capital and labour, but that the realization of its productivity-enhancing effects depends on complementary infrastructure, technological adaptation and the efficiency with which energy reaches productive users.

Renewable energy installation exhibits a delayed but economically meaningful contribution to manufacturing output. The insignificant contemporaneous effect, followed by a positive and statistically significant effect at the third lag, suggests that increases in installed renewable capacity do not immediately translate into higher manufacturing output. Instead, the productive benefits emerge after firms and the electricity system have had sufficient time to absorb and utilize the additional capacity. This is economically plausible because installed capacity represents the physical potential to generate electricity rather than electricity that is immediately available for productive use. New renewable infrastructure may require commissioning, grid connection, technical integration, adjustments in production processes and, in some cases, workforce training before its productive potential is realized. The negative coefficients observed during some short-run adjustment periods in the ECM further suggest that the transition itself may impose temporary adjustment costs before the benefits materialize. The finding therefore gives practical meaning to the distinction between energy capacity expansion and effective productive energy availability: increasing renewable capacity is necessary for industrial transformation, but its contribution to manufacturing becomes

meaningful only when the capacity is operationally integrated into the electricity system and effectively utilized by firms. This is consistent with infrastructure investment theory, in which investment may initially generate adjustment and implementation costs before yielding productivity gains.

Renewable energy generation similarly demonstrates a dynamic rather than instantaneous relationship with manufacturing output. The absence of an immediate statistically significant effect, together with positive and statistically significant effects emerging after two periods, indicates that increased renewable electricity generation requires time before its productive contribution becomes evident in manufacturing. This may occur because electricity generated by renewable sources must first be transmitted, distributed and synchronized with industrial demand before it can support continuous production. Manufacturing processes often depend not only on the quantity of electricity available but also on its reliability, quality and timing. Therefore, additional generation that is not adequately integrated into the grid may have limited immediate productive value. The emergence of positive lagged effects therefore suggests that the economic value of renewable generation increases as electricity becomes more reliably available and firms adjust production systems to exploit it. At the same time, the presence of negative coefficients at some later lags indicates that greater generation does not automatically guarantee proportionate increases in manufacturing output. Such patterns may reflect intermittency, grid constraints, demand-supply mismatches or periods in which additional generation exceeds the capacity of the existing system to transmit and productively absorb it. The broader implication is that generation capacity and industrial productivity are connected through the electricity system rather than through generation alone. This provides an important economic explanation for why investments in generation need to be accompanied by corresponding investments in transmission, distribution, storage, grid flexibility and industrial energy management.

Renewable energy consumption provides stronger evidence of the importance of actual energy utilization for manufacturing performance. Unlike installed capacity and generation, which represent energy-system potential and supply respectively, consumption captures the extent to which renewable energy is actually taken up within the economy. The positive and statistically significant long-run relationship therefore suggests that renewable energy contributes more meaningfully to manufacturing performance when it is effectively converted into productive economic activity. The lagged nature of the significant effects further indicates that firms may

require time to reorganize production processes, adopt energy-efficient technologies, adjust operating capacity and integrate renewable electricity into existing production systems. The short-run ECM results complement this finding by showing that current consumption can support manufacturing activity while some lagged consumption effects may temporarily be negative. Such short-run reversals can arise from adjustment costs, production restructuring, temporary inefficiencies or periods in which additional energy use does not immediately translate into proportional increases in output. The results imply that the economic value of renewable energy is ultimately realized through productive utilization rather than through the mere expansion of energy infrastructure. This has an important implication for the energy-growth relationship: renewable energy policy should move beyond increasing supply and pay greater attention to how effectively manufacturing firms can access, manage and convert renewable electricity into output.

Transmission-distribution losses represent an important constraint on the realization of renewable energy's productive potential. The consistently negative and statistically significant long-run effects indicate that persistent electricity losses undermine manufacturing performance even when renewable energy capacity and generation are expanding. This finding has a clear economic implication because electricity generated at the source does not constitute a productive input for manufacturing unless it reaches firms in usable quantities and with sufficient reliability. High transmission-distribution losses therefore create a gap between electricity produced and electricity effectively available to industrial users. The positive lagged effects observed in the short-run ECM should not be treated as evidence that losses are economically beneficial. Rather, they may capture periods in which higher electricity flows, rising electricity demand and increased economic activity occur simultaneously with greater measured system losses, or may reflect temporary responses by the electricity system and firms to changing supply conditions. The contrast between the short-run and long-run results is particularly informative: temporary positive statistical associations do not offset the structural long-run cost of an inefficient electricity network. The finding therefore strengthens the argument that renewable energy expansion and grid efficiency must be treated as complementary components of the energy value chain. Without reducing transmission-distribution losses, part of the economic value created through renewable generation and installation may fail to reach manufacturing firms.

The ARDL-ECM results provide evidence that renewable energy value chain dynamics affect manufacturing through a sequence of interconnected stages: installation creates energy-system capacity, generation makes renewable electricity available, consumption converts that availability into productive use, while transmission-distribution determine how effectively the energy reaches final users. The different timing of the estimated effects is therefore economically meaningful rather than merely a statistical irregularity. Installation and generation require time to translate into manufacturing activity because infrastructure must be commissioned, integrated and utilized, whereas consumption is more directly connected to productive activity. At the same time, transmission-distribution losses can weaken the conversion of energy-system expansion into actual industrial output. The findings therefore support a more integrated treated of renewable energy value chain dynamics in which energy availability, accessibility, reliability and productive utilization jointly determine its contribution to manufacturing performance.

In relation to the study hypotheses, the findings provide evidence for rejecting the relevant null hypotheses where the ARDL-ECM coefficients are statistically significant at the pre-specified 5% level. The evidence is particularly strong for the delayed effects of renewable energy installation and generation, the contribution of renewable energy consumption and the constraining long-run effect of transmission-distribution losses. Conversely, statistically insignificant contemporaneous coefficients do not provide sufficient evidence to reject the corresponding null hypotheses for those specific short-run relationships. The results therefore do not support the proposition that renewable energy value chain dynamics affect manufacturing output uniformly or instantaneously. Instead, they support the alternative proposition that specific components of the renewable energy value chain dynamics have statistically significant effects on manufacturing performance, with the timing and direction of those effects varying across the energy value chain chain.

From a theoretical perspective, the findings reinforce the view that energy functions as an important productive input within the production process, but that its contribution is mediated by complementary capital, infrastructure, technology and labour. The delayed benefits associated with renewable energy installation and generation are consistent with the idea that productive capacity does not automatically translate into output without complementary investments and technological adjustment. Similarly, the importance of renewable energy consumption suggests that energy contributes to manufacturing performance when it is

incorporated into productive processes rather than merely made available. The findings therefore provide empirical support for the broader logic of the Solow-Swan framework, in which technological and capital-related improvements enhance productivity when combined with other productive inputs, while also reflecting the endogenous-growth perspective, under which infrastructure, technological adoption and efficiency improvements can influence the productive capacity of the economy. The results from transmission-distribution losses are particularly important because they demonstrate that the productivity effects of energy investment depend not only on the quantity of energy supplied but also on the efficiency of the infrastructure through which that energy is delivered.

The findings are broadly consistent with the existing empirical literature. Obange et al. (2013) and Hoang et al. (2020) highlight the positive role of renewable energy development in supporting industrial productivity, while Kasae (2014) and Onuonga et al. (2008) emphasize the contribution of infrastructure investment to manufacturing output and technological adoption. Similarly, Forkuoh and Li (2015) and Grainger and Zhang (2017) support the broader argument that energy development can strengthen industrial resilience and sustainability. This study extends this literature by demonstrating that the relationship is not simply a contemporaneous energy-output relationship. Rather, the evidence shows that the timing of infrastructure deployment, generation, consumption and electricity losses matters considerably for manufacturing performance. In particular, incorporating transmission-distribution losses into the renewable energy-growth framework reveals an important channel through which inefficiencies in the electricity system can weaken the productive benefits of renewable energy expansion.

The findings also have clear policy and practical implications. Policies aimed at expanding renewable energy capacity should be accompanied by efficient grid integration, transmission-distribution upgrades, appropriate commissioning schedules and measures that facilitate productive energy utilization by manufacturing firms. The delayed positive effects of installation and generation imply that policymakers should not evaluate renewable energy investments solely on the basis of their immediate contribution to industrial output. Instead, sufficient time should be allowed for infrastructure commissioning, grid integration and firm-level adaptation. At the same time, the significant long-run effect of transmission-distribution losses demonstrates that expanding generation without improving electricity delivery may limit the extent to which renewable energy contributes to manufacturing growth. Ultimately,

importance of renewable energy consumption suggests that policies should encourage firms to adopt technologies and production systems capable of effectively utilizing renewable electricity. The central policy lesson is therefore that renewable energy expansion, grid efficiency and productive energy utilization should be pursued as complementary elements of industrial policy rather than as separate interventions.

Regarding model adequacy, the diagnostic and specification results provide no evidence of a serious econometric problem that would undermine the estimated relationships, subject to the specific diagnostic tests reported in the study. Estimating the manufacturing sector separately from agriculture and services also allows the renewable-energy effects to be identified within the sector-specific production environment rather than being obscured by aggregation across sectors. This strengthens the treatment of the results by recognizing that the productive role of renewable energy can differ according to the structure, energy intensity and adjustment characteristics of individual sectors.

The manufacturing sector results show that the transition to renewable energy is economically meaningful, but its benefits are neither automatic nor instantaneous. Renewable energy installation and generation require time to translate into productive manufacturing activity; renewable energy consumption provides a more direct link between energy use and output; and transmission-distribution losses represent a structural constraint that can weaken the benefits of energy-system expansion. The evidence therefore suggests that Kenya's renewable energy transition can contribute to manufacturing development most effectively when expansion of renewable capacity is accompanied by reliable grid integration, reduced electricity losses and increased productive utilization of renewable energy. This provides a more nuanced explanation of the renewable energy–manufacturing relationship than a simple positive or negative association and demonstrates why the quality, accessibility and utilization of renewable energy infrastructure are as important as its expansion.

4.6.2 Renewable Energy Value Chain Dynamics and the Service Sector

The findings indicate that renewable energy value chain dynamics exert differentiated and time-dependent effects on services-sector performance in Kenya, with the economic significance of installation, generation, consumption and transmission-distribution losses depending on whether the relationship is considered in the short run or over the longer adjustment process. This differentiation is economically meaningful because the services

sector depends heavily on electricity for ICT, financial services, commerce, hospitality, education, communication and other technology-intensive activities. Therefore, the productive contribution of renewable energy depends not only on the expansion of energy capacity but also on how quickly additional capacity is integrated, how much electricity is generated and consumed and how efficiently it reaches final users.

Renewable energy installation demonstrates an immediate positive short-run contribution to services-sector output. The ECM coefficient is positive and statistically significant, with a 1% increase in installed renewable energy capacity associated with an approximately Ksh 3.968 billion increase in services-sector output. This finding suggests that the services sector can respond relatively quickly to additional renewable energy infrastructure because many service activities can incorporate additional electricity capacity without the lengthy physical production adjustments associated with more energy-intensive industries. Expansion of renewable capacity can support digital infrastructure, telecommunications, financial technologies, commercial operations, refrigeration, lighting and other electricity-dependent activities. The absence of statistically significant lagged installation effects in the ARDL estimates further suggests that the principal effect of installation occurs around the period in which the additional capacity becomes available rather than through a prolonged sequence of subsequent effects. This indicates that for the services sector, the installation stage of the renewable energy value chain can generate relatively rapid productivity benefits when new capacity is effectively connected to productive users.

Renewable energy generation presents a more complex dynamic relationship with services-sector output. The ARDL estimates indicate an insignificant contemporaneous association and negative statistically significant effects at the second and third lags, while the ECM estimates reveal an insignificant contemporaneous effect followed by positive and statistically significant effects after one and two years. Rather than treating these results as contradictory, they indicate that the relationship between generation and services-sector performance changes across the adjustment process captured by the two models. In the immediate period, additional generation does not automatically translate into higher service output because electricity must first be transmitted, distributed and incorporated into productive activities. The positive ECM lagged effects suggest that once firms and the electricity system adjust, increased renewable generation can contribute positively to services-sector activity. At the same time, the negative longer-lag coefficients in the ARDL dynamic specification indicate that the benefits of generation are not

necessarily uniform over time. This may reflect differences between electricity generation and actual utilization, supply-demand mismatches, grid constraints or changes in the composition of service activities. The economic implication is therefore that generation alone is insufficient to guarantee sustained services-sector gains; its contribution depends on effective integration, reliable delivery and productive absorption of the electricity generated.

Renewable energy consumption provides the clearest evidence that actual utilization of renewable energy is central to services-sector performance. The contemporaneous consumption coefficient is positive and statistically significant in the ARDL specification, indicating that a one-MW increase in renewable energy consumption is associated with an approximately Ksh 60.264 billion increase in current services-sector output, holding other factors constant. This relationship is economically intuitive because consumption represents the point at which renewable energy is actually incorporated into economic activity. Unlike installation, which represents capacity, or generation, which represents electricity supply, consumption captures the extent to which available renewable energy is actively used by productive agents. The finding therefore suggests that the economic benefits of the renewable energy value chain become most visible when electricity is converted into productive services such as digital transactions, communication, financial intermediation, retail, hospitality and other commercial activities. The strong contemporaneous relationship also indicates that the services sector may have relatively high responsiveness to actual electricity availability because many of its activities can adjust rapidly when energy inputs become available. Thus, the key economic distinction is between having renewable energy infrastructure and actually using the energy it provides.

Transmission-distribution losses require particularly cautious treatment because their estimated signs differ across the short-run and longer dynamic relationships. In the ARDL specification, the contemporaneous coefficient is statistically insignificant, while the lagged coefficients are negative but also statistically insignificant at the 5% level. On the other hand, the ECM produces positive and statistically significant coefficients at the first and second lags. These results do not provide evidence that higher electricity losses improve services-sector performance. Instead, the positive short-run lagged associations may reflect the broader relationship between electricity flows, electricity demand and economic activity. Periods of expanding electricity use may coincide with increased system flows and therefore, higher measured losses, even while services-sector activity is expanding. The absence of statistically

significant negative ARDL effects also means that the study should avoid claiming that transmission-distribution losses have a statistically established detrimental short-run effect on services output. Nevertheless, from an economic and infrastructure perspective, persistent electricity losses remain an important efficiency concern because electricity generated but lost before reaching users cannot directly support productive activity. The statistical results do not establish a beneficial effect of losses, while the economic rationale continues to support improvements in grid efficiency as a means of ensuring that renewable energy generated is converted into usable electricity for service-sector activities.

The combined ARDL-ECM evidence therefore reveals an important energy-transition chain within the services sector. Installation has an immediate positive short-run association with output, indicating that the sector can respond rapidly when additional renewable capacity becomes operational. Generation requires a longer adjustment process, with positive short-run effects emerging after one and two years, while its dynamic ARDL coefficients indicate that the relationship is not uniform across time. Consumption has the strongest direct connection with current services-sector activity because it captures actual productive utilization of renewable energy. Transmission-distribution losses, meanwhile, highlight the importance of the delivery stage of the energy system, although the estimated coefficients do not provide sufficient evidence at 5% to characterize losses as a statistically established negative short-run determinant of services output. The broader economic meaning is that renewable energy contributes to services-sector performance most effectively when capacity expansion is translated into reliable and productive electricity consumption through an efficiently functioning electricity network.

The ECM results further strengthen this assertion by demonstrating that short-run changes occur around an underlying adjustment process. The ECM coefficient of -0.156 is negative and statistically significant, indicating that approximately 15.552% of the previous period's disequilibrium is corrected within one year. This relatively modest adjustment speed suggests that the services sector does not immediately return to its long-run equilibrium path following a disturbance. Instead, adjustment occurs gradually, with the remaining disequilibrium being corrected progressively over subsequent periods. This gradual adjustment is plausible because changes in renewable energy infrastructure, electricity use, investment decisions and service-sector production do not instantaneously translate into a new equilibrium. Firms may require time to alter technology, contracts, operating arrangements and investment decisions, while the

electricity system may require time to adjust supply and demand. The negative and significant error-correction coefficient demonstrates convergence towards the estimated equilibrium relationship, but the existence of cointegration should be established from the ARDL bounds test, since the output explicitly notes that the reported error-correction p-value is incompatible with the Bounds distribution.

In relation to the study hypotheses, the evidence supports rejection of the relevant null hypotheses where the estimated coefficients are statistically significant at the prespecified 5% level. In particular, the significant short-run effect of renewable energy installation and the significant contemporaneous effect of renewable energy consumption provide evidence that these components of the renewable energy value chain influence services-sector output. Renewable energy generation also exhibits significant effects at specific lags, demonstrating that its influence is not confined to the contemporaneous period. For transmission-distribution losses, however, the results should be treated more cautiously because the estimated lagged ECM coefficients are positive and significant, whereas the ARDL coefficients do not establish a statistically significant negative relationship at the 5% level. The appropriate conclusion is therefore not that the null hypothesis concerning losses is uniformly rejected, but that the evidence for the effect of transmission-distribution losses depends on the dynamic specification and should not be treated as evidence that higher losses improve services-sector performance. The findings support the alternative hypothesis that at least some components of renewable energy value chain exert statistically significant effects on services-sector performance.

From a theoretical perspective, the findings reinforce the view that energy is a productive input whose contribution depends on its interaction with other factors of production and supporting infrastructure. The strong relationship between renewable energy consumption and services-sector output is consistent with the production-function perspective in which energy complements labour, capital and technology in generating output. The delayed generation effects further support the idea that infrastructure and technological investments may require time before their productivity effects are realized. The findings also provide an important qualification to a simple energy-output relationship: energy availability is not equivalent to productive energy utilization. The economic contribution of renewable energy is greatest when installed capacity is operational, electricity is generated reliably, energy reaches productive users and firms are capable of incorporating it into their production processes.

The findings are broadly consistent with previous empirical evidence. Zahoor et al. (2022) and Adedoyin et al. (2020) demonstrate the contribution of renewable energy development to service-sector performance through improved energy access and reliability, while Bayraktutan et al. (2011) and Guja-Huseynli (2023) emphasize the productivity and operational-efficiency benefits associated with energy infrastructure investment. Ásványi et al. (2017) similarly highlights the role of renewable energy in supporting sustainable and resilient performance in service-based activities. This study extends this literature by showing that the renewable energy–services relationship is not simply contemporaneous. Instead, different components of the value chain operate at different speeds: installation can generate relatively immediate benefits, generation may require adjustment before its productive effects emerge, consumption has a particularly strong direct association with output and the efficiency of electricity delivery influences how effectively energy-system expansion can be translated into economic activity.

The robustness and diagnostic results further support the reliability of the estimated relationships, subject to the specific diagnostic tests reported in the study. The absence of evidence of serious endogeneity or omitted-variable problems strengthens confidence that the observed relationships are not simply the result of obvious specification deficiencies. Moreover, estimating the services sector separately from agriculture and manufacturing avoids concealing sector-specific responses that could arise from using aggregate output. This sector-specific approach is particularly important because services differ from agriculture and manufacturing in their energy intensity, production structure and ability to respond rapidly to changes in electricity availability.

From a policy perspective, the findings suggest that renewable energy policy for the services sector should focus not merely on expanding installed capacity but on converting that capacity into reliable and productive energy use. The immediate positive effect of installation indicates that timely deployment and grid connection of renewable capacity can support service-sector activity. However, the lagged generation results demonstrate the importance of complementary investments in transmission, distribution, grid management and demand-side integration. The strong relationship between renewable energy consumption and services output further suggests that policies should facilitate productive electricity use by service-sector firms, including through reliable electricity access, digital infrastructure and energy-efficient technologies. Although the statistical results do not establish a negative short-run effect of transmission-distribution losses at the 5% level, improving grid efficiency remains

economically important because reducing losses increases the proportion of generated electricity that ultimately reaches productive users.

The services-sector findings demonstrate that renewable energy value chain is economically meaningful but operates through different channels and adjustment periods. The sector responds relatively quickly to renewable energy installation, while the productive benefits of generation become more apparent after adjustment. Actual renewable energy consumption has the strongest immediate productive association, emphasizing that the ultimate economic value of renewable energy lies in its utilization rather than in capacity expansion alone. The results therefore suggest that Kenya can obtain greater services-sector benefits from the renewable energy value chain when investment in renewable capacity is accompanied by reliable grid integration, efficient electricity delivery and measures that enable firms to convert renewable electricity into productive economic activity. This interpretation gives the findings greater economic meaning while avoiding the assumption that every renewable-energy indicator should have the same direction or timing of effect.

4.6.3 Renewable Energy Value Chain Dynamics and the Agriculture Sector

The findings indicate that renewable energy value chain dynamics have complex, time-dependent and sector-specific implications for agricultural performance in Kenya. Unlike the services sector, where some renewable energy effects emerge relatively quickly, agriculture appears to require a period of adjustment before renewable energy inputs translate into measurable productive gains. This is economically plausible because agricultural production depends on the interaction of energy with land, water, machinery, weather conditions, storage facilities and processing infrastructure. Thus, an increase in renewable energy capacity or consumption does not necessarily translate immediately into higher agricultural output. Rather, the productive value of renewable energy depends on whether farmers and agro-processing activities can effectively incorporate the additional energy into irrigation, mechanization, drying, refrigeration, storage and other stages of the agricultural value chain.

Renewable energy installation demonstrates the clearest adjustment pattern in the agricultural sector, with an initial negative effect followed by a positive delayed effect. The statistically significant negative contemporaneous coefficient indicates that a 1% increase in installed renewable energy capacity is associated with an approximately Ksh 1.987 billion decrease in agricultural value added in the current period. This short-run negative association can be understood as an adjustment cost associated with the deployment of energy infrastructure.

Renewable energy projects may require land allocation, construction activity, installation of equipment, changes in land use and temporary disruption of existing agricultural operations before the infrastructure becomes fully productive. The positive and statistically significant first-lag coefficient, however, indicates that a 1% increase in installed renewable energy capacity one year earlier is associated with an approximately Ksh 2.614 billion increase in current agricultural value added. The reversal from a negative contemporaneous effect to a positive lagged effect is economically important because it suggests that the agricultural benefits of renewable energy installation emerge after the initial deployment costs have been absorbed. Once the infrastructure becomes operational, renewable energy can support irrigation, mechanized farming, water pumping, post-harvest handling, refrigeration and agro-processing. The finding therefore provides empirical support for an investment-adjustment mechanism in which infrastructure initially imposes transitional costs but subsequently expands the productive capacity of agriculture.

Renewable energy generation, on the other hand, does not provide statistically established evidence of a short-run effect on agricultural value added at the 5% level. The contemporaneous coefficient is negative but insignificant, while the lagged coefficients alternate in sign and remain statistically insignificant at the study's prespecified 5% level. This pattern suggests that generating more renewable electricity at the source is not, by itself, sufficient to generate measurable agricultural productivity gains. The economic explanation is particularly relevant for agriculture because electricity must reach geographically dispersed farms and agricultural enterprises before it can be converted into productive output. Generation therefore represents available energy supply rather than actual productive utilization. Without appropriate transmission-distribution infrastructure, irrigation systems, electric machinery, cold storage, processing facilities and other energy-dependent technologies, additional generation may have limited immediate influence on agricultural production. The absence of a statistically significant generation effect hence does not imply that renewable electricity is economically irrelevant to agriculture; rather, it suggests that generation must be connected to productive agricultural uses before its contribution becomes measurable in sectoral output. This finding gives particular importance to complementary investments such as agricultural mini-grids, solar-powered irrigation, electric processing equipment and decentralized energy systems.

Renewable energy consumption provides stronger evidence of the productive importance of actual energy utilization in agriculture. Although the contemporaneous consumption coefficient is negative and statistically insignificant, the first lag is positive and statistically significant, with a one-MW increase in renewable energy consumption one year earlier associated with an approximately Ksh 10.899 billion increase in current agricultural value added. The delayed response is economically meaningful because agricultural energy use often generates benefits through production processes that take time to affect measured sectoral output. For example, renewable electricity used for irrigation can influence crop production over a subsequent growing cycle, while energy used for drying, refrigeration, storage and processing can affect output and value added after harvesting. The result therefore suggests that the productive effect of renewable energy consumption is not necessarily immediate because agricultural production itself operates through biological and production cycles. This provides a stronger economic interpretation than simply stating that consumption has a positive lagged coefficient: renewable energy becomes productive when it is embedded in agricultural processes whose output materializes over time. The finding is consistent with agricultural production theory, in which energy complements land, labour and capital rather than functioning as an isolated determinant of output.

Transmission-distribution losses produce an unexpected positive statistical relationship with agricultural value added. The contemporaneous ECM coefficient is positive and statistically significant, with a 1% increase in transmission-distribution losses associated with an approximately Ksh 1.036 billion increase in agricultural value added. However, the corresponding ARDL contemporaneous and lagged coefficients are not statistically significant at the 5% level. The positive ECM coefficient therefore should not be treated as evidence that electricity losses increase agricultural productivity. Rather, it may capture co-movement between electricity-system activity and agricultural output. Periods of increasing electricity demand and electricity throughput may simultaneously generate higher measured system losses and greater agricultural activity. In addition, agricultural producers may respond to unreliable grid electricity by using alternative energy sources, including diesel-powered equipment, solar systems, mini-grids and other decentralized technologies, allowing production to continue despite weaknesses in the central electricity network. Such adaptive behaviour can weaken the direct observed relationship between grid losses and agricultural output. Nevertheless, from an economic-efficiency perspective, electricity losses remain undesirable because energy lost before reaching productive users represents a loss of potentially productive resources and can

increase the effective cost of electricity. The finding should therefore be seen as an empirical statistical association rather than a productivity benefit from higher losses.

The combined ARDL-ECM findings reveal an important feature of the agricultural energy transition: the productive value of renewable energy depends heavily on timing, accessibility and utilization. Installation produces an initial adjustment cost before generating a positive effect after one year; generation alone does not produce statistically established short-run effects; and consumption produces a positive effect after a one-year delay. These results are consistent with the structure of agricultural production, where energy must be incorporated into activities such as irrigation, mechanization, processing and storage before its contribution becomes visible in sectoral value added. The findings therefore suggest that the agricultural sector does not respond simply to the quantity of renewable energy available in the national system. Instead, the critical issue is whether renewable energy is converted into productive agricultural energy services. This distinction helps explain why installation and consumption produce stronger evidence than generation alone.

The error-correction dynamics reinforce the importance of adjustment in the agricultural sector. The ECM coefficient of -1.075 is negative and highly statistically significant, indicating a very strong adjustment mechanism towards the estimated long-run equilibrium relationship. In absolute terms, the coefficient implies that approximately 107.485% of the previous period's disequilibrium is corrected within one year. Because the adjustment coefficient exceeds unity in absolute value, the correction process involves overshooting rather than a simple gradual return to equilibrium. This means that when agricultural output and the renewable-energy-related explanatory variables move away from their long-run equilibrium path, the subsequent adjustment is sufficiently strong to eliminate the previous disequilibrium and move the system beyond the equilibrium position before subsequent periods correct the resulting deviation. This can be seen as evidence of a highly responsive but potentially oscillatory adjustment process. Such behaviour is plausible in agriculture because production responses can be affected by seasonal production cycles, investment timing, weather-related conditions, input adjustments and changes in energy availability. The coefficient does not mean that 107.485% of agricultural output is literally “restored”; rather, it measures the proportion of the previous period's disequilibrium from the estimated long-run relationship that is corrected through the adjustment mechanism. The negative sign is essential because it indicates convergence, while the magnitude greater than one indicates that the convergence occurs through overshooting.

The negative and statistically significant ECM coefficient provides strong evidence of an adjustment mechanism, but it should not by itself be used as the sole basis for establishing cointegration, particularly where the software reports that the associated p-value is incompatible with the t-Bounds distribution. The bounds test provides the appropriate formal basis for determining whether a stable long-run relationship exists. Once cointegration is established, the magnitude of -1.075 becomes economically meaningful as evidence that agricultural-sector deviations from the long-run path are corrected rapidly, albeit through an overshooting adjustment process.

In relation to the study hypotheses, the findings provide evidence for rejecting the relevant null hypotheses where the estimated relationships are statistically significant at the prespecified 5% level. Renewable energy installation demonstrates significant effects in both the contemporaneous and lagged periods, although the signs differ, while renewable energy consumption produces a statistically significant positive effect after one year. Renewable energy generation does not provide sufficient evidence of a statistically significant effect at 5%, despite some coefficients being suggestive at the 10% level. Transmission-distribution losses require particular caution: although the contemporaneous ECM coefficient is positive and statistically significant, the ARDL estimates do not establish a consistent statistically significant effect. Thus, the results should not be presented as evidence that losses systematically improve agricultural performance. The findings support the alternative hypothesis that specific components of renewable energy value chain significantly influence agricultural performance, with the strongest evidence arising from the timing of renewable energy installation and actual renewable energy consumption.

From a theoretical perspective, the agricultural findings reinforce the idea that energy operates as a complementary productive input rather than as an independent source of output growth. Renewable energy becomes economically productive when it interacts with capital, labour, land and agricultural technologies. The delayed positive effects of installation and consumption are particularly consistent with investment and production theories because productive infrastructure requires complementary inputs and time before its full productivity benefits are realized. The results also demonstrate that infrastructure expansion and productive utilization are not synonymous. A country may increase renewable electricity generation without achieving equivalent agricultural gains if farmers lack the infrastructure and technologies required to access and utilize that energy. Thus, the findings provide an important qualification

to the conventional energy-growth relationship by demonstrating that the pathway from renewable energy expansion to agricultural output runs through access, utilization and complementary productive investment.

The findings are broadly consistent with previous research. Obange (2019) and Sartbayeva et al. (2023) emphasize the contribution of renewable energy access to agricultural mechanization and productivity, while Liang et al. (2020) and Smagulova et al. (2023) highlight the role of sustainable energy in improving efficiency across agricultural activities. Similarly, Zou (2022) and Zhang et al. (2019) highlight the contribution of renewable energy adoption to climate-resilient practices and long-term agricultural performance. This study extends these findings by demonstrating that the energy-agriculture relationship is not uniform across the renewable energy value chain or across time. In particular, the evidence that installation initially imposes a cost before generating a positive effect, together with the delayed effect of consumption, provides a dynamic explanation for why the benefits of renewable energy adoption may not be immediately observable in agricultural output.

The robustness and diagnostic results provide no indication that the estimated agricultural relationships are driven by serious endogeneity, omitted-variable problems or unaccounted-for structural changes, subject to the specific diagnostic tests reported in the study. Estimating agriculture separately also prevents the distinctive characteristics of agricultural production from being masked by the inclusion of manufacturing and services in an aggregate output measure. This sector-specific approach is important because agriculture has different production cycles, energy requirements and adjustment mechanisms from the other productive sectors.

From a policy perspective, the results suggest that renewable energy policy for agriculture should move beyond capacity expansion towards productive energy utilization. The initial negative effect of installation implies that policymakers should anticipate and manage transitional costs associated with renewable energy infrastructure deployment, particularly where projects interact with agricultural land and existing production activities. The subsequent positive effect demonstrates why such short-run costs should be evaluated alongside the longer-term productive benefits. Similarly, the insignificant generation effects indicate that expanding renewable electricity generation without connecting it to agricultural users may produce limited sectoral gains. Investments in solar-powered irrigation, agricultural mini-grids, electric machinery, cold storage, drying and agro-processing facilities can help convert renewable

electricity into measurable agricultural productivity. Improving transmission-distribution efficiency remains equally important, although the empirical results do not justify claiming that losses have a statistically established negative effect on agricultural output in this specification.

The agricultural-sector findings demonstrate that renewable energy transition generates benefits through an adjustment process rather than an instantaneous transformation of agricultural output. Installation initially imposes measurable short-run adjustment costs but produces positive effects after one year; generation alone does not provide statistically established short-run gains; and renewable energy consumption produces a significant positive effect after a one-year delay. The very strong error-correction coefficient further indicates that agricultural output adjusts rapidly towards the estimated long-run equilibrium, although the adjustment occurs through overshooting. The central economic implication is therefore that Kenya's renewable energy transition can contribute substantially to agricultural development when energy infrastructure is accompanied by productive technologies, reliable access and sufficient time for agricultural producers to integrate renewable energy into their production processes. This provides a more meaningful interpretation of the results than treating renewable energy simply as an additional source of electricity: its ultimate contribution to agriculture depends on how effectively the energy is integrated into the agricultural production system.

4.7 Alignment of Study Findings with National, Regional and Global Development Frameworks

Objective One sought to determine the effect of renewable energy constructs; installation, generation, consumption and transmission-distribution losses on manufacturing-sector performance in Kenya. The findings demonstrate that renewable energy value chain dynamics influence manufacturing performance through differentiated and time-dependent channels. The delayed positive effects of renewable energy installation and generation, together with the positive contribution of renewable energy consumption and the constraining role of transmission-distribution losses, indicate that expanding renewable energy capacity alone is insufficient to guarantee industrial gains. Rather, the productive benefits of the transition depend on effective integration, utilization and delivery of electricity. These findings are consistent with Kenya Vision 2030, which identifies reliable and affordable energy infrastructure as an important enabler of industrialization, productivity and economic competitiveness. At the global level, the findings support SDG 7 on Affordable and Clean Energy through the expansion and utilization of renewable energy, SDG 8 on Decent Work

and Economic Growth through improved productive-sector performance and SDG 9 on Industry, Innovation and Infrastructure through the interaction between energy infrastructure and industrial development. They also complement the objectives of the Paris Agreement of 2015 by demonstrating the economic importance of transitioning towards cleaner energy systems. At the continental level, the findings are consistent with Africa Agenda 2063, particularly Aspiration 1, which seeks inclusive growth and sustainable development. The manufacturing results therefore demonstrate that Kenya's renewable energy transition can contribute to industrial transformation when capacity expansion is accompanied by efficient transmission, distribution and productive utilization.

Objective Two sought to determine the effect of renewable energy constructs on services-sector performance in Kenya. The findings indicate that the services sector responds differently to the various components of renewable energy value chain. Renewable energy installation produces an immediate positive short-run effect, while renewable energy generation produces significant effects with a time lag and renewable energy consumption provides a direct channel through which energy utilization supports service-sector activity. The results further demonstrate that energy-system inefficiencies can influence service-sector performance, highlighting the importance of reliable electricity delivery alongside capacity expansion. These findings align with Kenya Vision 2030, which recognizes infrastructure, information and communication technologies, financial services and other modern service activities as important components of Kenya's economic transformation. Internationally, the findings support SDG 7 by emphasizing reliable and sustainable energy use, SDG 8 through the contribution of energy availability and utilization to economic activity and SDG 9 through the importance of energy and digital infrastructure to modern service-sector development. They are also consistent with the Paris Agreement, which encourages transitions towards low-carbon development pathways. At the continental level, the findings correspond with Africa Agenda 2063's emphasis on inclusive growth, modern infrastructure and sustainable economic transformation. The services-sector results therefore demonstrate that renewable energy contributes to service-sector development most effectively when installed capacity is translated into reliable and productive energy use.

Objective Three sought to determine the effect of renewable energy constructs on agricultural-sector performance in Kenya. The findings reveal a particularly time-dependent relationship, with renewable energy installation initially associated with short-run adjustment costs but followed by positive effects, while renewable energy consumption produces positive effects

after a lag. Renewable energy generation does not exhibit a consistent statistically significant short-run effect, demonstrating that generation alone does not guarantee productive gains in agriculture. The findings therefore emphasize the importance of converting renewable energy availability into effective agricultural use through irrigation, mechanization, processing, drying and storage, while improving the efficiency of electricity delivery. This evidence is consistent with Kenya Vision 2030, which identifies agricultural transformation, productivity improvement and infrastructure development as central to national economic development. At the global level, the findings support SDG 7 through sustainable energy utilization and SDG 12 on Responsible Consumption and Production through more efficient use of energy resources. They also complement the Paris Agreement's emphasis on climate-resilient and low-carbon development. At the continental level, the findings are consistent with Africa Agenda 2063, particularly its emphasis on sustainable development, agricultural transformation and environmentally sustainable economic growth. The agricultural results therefore demonstrate that renewable energy can support agricultural transformation, but the realization of these benefits depends on effective utilization, complementary productive infrastructure and efficient energy delivery.

The three objectives demonstrate that renewable energy transition is relevant to Kenya's national, regional and global development priorities, but its contribution to sectoral performance is neither automatic nor uniform. The empirical evidence shows that installation, generation, consumption and transmission-distribution losses operate through different channels and time horizons across manufacturing, services and agriculture. This finding strengthens the relevance of Vision 2030, Africa Agenda 2063, the Sustainable Development Goals and the Paris Agreement, because it shows that achieving energy-related development objectives requires more than expanding renewable generation capacity. It requires the effective integration of renewable energy into the electricity system, efficient transmission-distribution and productive utilization across economic sectors. The findings therefore provide empirical support for Kenya's broader transition towards a reliable, efficient and sustainable energy system capable of translating renewable energy development into sector-specific economic gains. They also provide a basis for linking the study's recommendations to the National Energy Policy 2025–2034 and Kenya's continuing climate and sustainable-development commitments.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter offers a structured account of the key findings that emerged from the research derived from the analysis. The chapter further develops conclusions that are informed by the empirical evidence generated in the study and provides practical regulatory frameworks for adoption. This chapter also outlines the study's limitations and suggests areas for further research. It also provides the study's contributions to research, academia and policy.

5.2 Summary of Findings

5.2.1 Renewable Energy Value Chain Dynamics and the Manufacturing Sector

The findings for the manufacturing sector indicate that renewable energy value chain dynamics influence output performance in a largely time-dependent and structurally differentiated manner. Renewable energy installation does not exert an immediate effect on manufacturing performance, but its impact becomes positive and significant over time. This suggests that the benefits of infrastructure development are realized only after a period of adjustment, during which renewable energy installed capacity is integrated into production systems. In the short run, installation is associated with transitional disruptions, reflecting the adjustment costs faced by firms before productivity gains are achieved.

Renewable energy generation exhibits mixed effects, with no immediate impact but positive contributions emerging after a delay. This indicates that increased energy supply supports manufacturing activity only when it becomes stable and reliably accessible to firms. However, the presence of negative effects in later periods suggests underlying inefficiencies within the energy system, such as transmission constraints or mismatches between supply and industrial demand, which may limit the sustained contribution of generation to output performance.

Renewable energy consumption emerges as a central driver of manufacturing sector performance. The results show that energy use contributes positively to output, particularly over time, confirming that actual utilization of energy is the key channel through which renewable energy supports industrial productivity. The presence of negative short-run effects associated with past consumption highlights the existence of adjustment frictions, including inefficiencies in energy use and production constraints, which may temporarily dampen output.

Transmission-distribution losses are found to have a consistently adverse effect on manufacturing output, especially in the long run. This indicates that inefficiencies within the energy system reduce the effective availability of electricity for production and undermine the gains associated with renewable energy expansion. Although short-run dynamics suggest the presence of temporary adjustment responses, these do not offset the long-term negative implications of energy losses.

The findings demonstrate that renewable energy contributes to manufacturing sector performance through a gradual and adjustment-driven process. While installation and consumption support output expansion over time, the effectiveness of generation is constrained by system inefficiencies and energy losses remain a significant barrier to sustained industrial performance. These results highlight the importance of not only expanding renewable energy capacity but also ensuring efficient delivery, integration and utilization within the manufacturing sector.

5.2.2 Renewable Energy Value Chain Dynamics and the Services Sector

The findings for the services sector indicate that renewable energy dynamics exert immediate but structurally differentiated effects on output performance in Kenya. Renewable energy installation plays a positive and short-lived role, with its impact largely confined to the contemporaneous period. This suggests that the services sector benefits quickly from newly installed energy infrastructure, reflecting its strong dependence on reliable and readily available electricity for operational activities. However, the absence of significant lagged effects implies that these gains are not sustained over time without continuous improvements in energy access and system efficiency.

Renewable energy generation is found to have a predominantly negative influence on services sector performance in the short run, particularly through its lagged effects. This indicates that increases in generation do not automatically translate into improved service output, largely due to inefficiencies in energy transmission, distribution constraints and potential mismatches between energy supply and sectoral demand. The findings highlight that generation capacity alone is insufficient to drive performance unless it is effectively integrated into the broader energy delivery system.

Renewable energy consumption emerges as the most consistent and influential driver of services sector performance. The results show that increased energy use directly enhances

output, underscoring the importance of effective energy utilization in supporting service-based economic activities. This reflects the central role of energy as a productive input in sectors such as ICT, finance, education and trade, where operational efficiency is closely tied to reliable power supply.

Transmission-distribution losses are found to negatively affect the services sector output, particularly over time. The lagged effects indicate that inefficiencies in energy delivery reduce the availability of usable electricity, increase operational costs and disrupt service provision. This highlights the importance of improving grid efficiency and minimizing losses to ensure that gains from renewable energy expansion are fully transmitted to the services sector.

The findings demonstrate that renewable energy contributes to the services sector performance primarily through immediate access and effective utilization, while inefficiencies in generation and energy delivery systems act as constraints. The results emphasize the need for policies that not only expand renewable energy capacity but also enhance system efficiency and ensure reliable energy supply to sustain growth in the services sector.

5.2.3 Renewable Energy Value Chain Dynamics and the Agriculture Sector

The findings for the agriculture sector reveal that renewable energy dynamics influence output through a strongly time-dependent adjustment process, with clear distinctions between short-run disruptions and longer-term productivity gains. Renewable energy installation is associated with an initial negative effect on agricultural output, reflecting adjustment costs such as disruptions to farming activities and resource reallocation during infrastructure development. However, this effect reverses over time, with installation contributing positively to output once fully integrated into agricultural production systems. This highlights the role of renewable energy infrastructure in supporting productivity-enhancing activities such as irrigation, mechanization, storage and agro-processing.

Renewable energy generation exhibits weak and inconsistent effects on agricultural output, with no clear evidence of a strong direct contribution. The results suggest that increases in energy generation alone are insufficient to drive agricultural growth, particularly in the absence of effective transmission systems and access mechanisms. This reflects the indirect nature of energy generation in agriculture, where productivity gains depend more on the accessibility and utilization of energy rather than its production at source.

Renewable energy consumption demonstrates a delayed but meaningful positive influence on agricultural output. While immediate effects are not evident, past energy use is associated with improvements in productivity, indicating that the benefits of energy utilization materialize over time. This finding highlights the importance of energy as a complementary input in agriculture, where its impact is realized through processes such as irrigation, processing and storage, which require time to translate into output gains.

Transmission-distribution losses present an unexpected but contextually explainable relationship with agricultural output. In the short run, higher losses are associated with increased output, likely reflecting underlying structural dynamics such as increased energy throughput or adaptive responses by farmers to unreliable grid supply. However, this relationship does not imply efficiency and from a theoretical perspective, persistent energy losses remain detrimental to productivity by reducing the availability of usable energy and increasing costs.

The findings indicate that renewable energy contributes to agricultural performance primarily through delayed integration and effective utilization, while generation inefficiencies and energy losses limit the full realization of these benefits. The findings emphasize the need for policies that enhance not only energy supply but also accessibility, efficiency and sector-specific utilization to support sustained agricultural productivity.

5.3 Conclusions

This study set out to examine the influence of renewable energy value chain dynamics on sectoral performance in Kenya, focusing on the manufacturing, services and agriculture sectors. The findings demonstrate that renewable energy plays a significant but complex role in shaping sectoral performance, with effects that vary across sectors and over time. Across all three sectors, the results consistently show that the contribution of renewable energy is not instantaneous, but rather unfolds through a process of adjustment, integration and utilization.

A key conclusion derived from the study is that renewable energy installation, while essential for expanding energy capacity, is associated with short-run adjustment costs before yielding positive productivity gains. This pattern is particularly evident in the manufacturing and agriculture sectors, where infrastructure deployment initially disrupts production but ultimately enhances output once fully integrated. On the other hand, the services sector benefits more immediately from installation, reflecting its greater responsiveness to improvements in energy access.

The study further establishes that renewable energy generation alone does not guarantee sectoral performance. Its impact is often weak or inconsistent, highlighting the presence of structural inefficiencies in energy transmission, distribution and sectoral alignment. This highlights the importance of moving beyond capacity expansion toward ensuring that generated energy is effectively delivered and matched with sector-specific demand.

Renewable energy consumption emerges as the most consistent and reliable driver of sectoral performance, confirming that actual utilization of energy is the primary channel through which renewable energy supports economic activity. Across all sectors, the results indicate that productivity gains are closely linked to the extent to which energy is efficiently used in production processes.

The findings highlight the critical role of energy efficiency, particularly in relation to transmission-distribution losses. Persistent losses undermine the effective supply of energy and constrain sectoral output, even in the presence of increased installation and generation. While some short-run dynamics reflect adaptive responses, the long-run implications of energy inefficiencies remain negative.

The study concludes that the effectiveness of renewable energy in driving sectoral performance in Kenya depends not only on expanding energy infrastructure, but also on ensuring efficient delivery systems, timely integration and productive utilization across sectors. These insights provide a strong foundation for policy interventions aimed at maximizing the developmental impact of renewable energy within the Kenyan economy.

5.4 Recommendations

5.4.1 Renewable Energy Value Chain Dynamics and the Manufacturing Sector

To enhance the contribution of renewable energy to manufacturing sector performance, the Ministry of Energy and Petroleum, in collaboration with the Ministry of Investments, Trade and Industry and the Special Economic Zones Authority (SEZA), should prioritize the development of industrial-based renewable energy systems, including solar rooftops, embedded generation and captive power plants within industrial parks, export processing zones and special economic zones. These institutions should incorporate renewable energy requirements into the planning and development of industrial zones and facilitate streamlined approval and connection procedures for firms investing in on-site renewable energy systems.

This would ensure that newly installed renewable energy capacity is directly linked to productive industrial use, thereby reducing delays between installation and utilization.

To address the lagged benefits of renewable energy installation identified in the study, the Kenya Revenue Authority (KRA), the Ministry of Investments, Trade and Industry and relevant financial institutions should develop targeted incentives for manufacturing firms investing in renewable energy infrastructure. Such measures could include accelerated depreciation allowances for qualifying renewable energy equipment, targeted tax incentives and concessional green financing. The incentives should be linked to the actual installation and productive utilization of renewable energy systems, with appropriate monitoring mechanisms to minimize the risk of firms acquiring capacity that remains underutilized. The Central Bank of Kenya (CBK) and participating financial institutions could further facilitate access to affordable financing by supporting the development of green-finance products tailored to manufacturing firms investing in renewable energy technologies.

Given the weak and inconsistent role of renewable energy generation in some manufacturing specifications, the Ministry of Energy and Petroleum, Kenya Electricity Transmission Company (KETRACO) and Kenya Power should prioritize grid modernization and improved electricity delivery to industrial users. In particular, KETRACO and Kenya Power should strengthen transmission-distribution infrastructure serving major industrial areas, while EPRA should strengthen regulatory oversight of electricity reliability and quality for productive-sector users. The deployment of smart-grid technologies, dedicated industrial feeders and improved load-management systems should be prioritized in areas with high concentrations of manufacturing activity. These measures would improve the reliability with which renewable electricity generated within the national system reaches manufacturing firms and reduce mismatches between electricity supply and industrial demand.

Since renewable energy consumption demonstrates a more direct relationship with manufacturing output, the Ministry of Investments, Trade and Industry, working with EPRA and the Kenya Association of Manufacturers (KAM), should strengthen programmes that promote efficient and productive use of renewable electricity within manufacturing firms. This should include periodic energy audits, adoption of energy-efficient machinery, improved energy-management systems and technical support for firms seeking to integrate renewable electricity into their production processes. EPRA should strengthen compliance with applicable energy-efficiency requirements, while KAM can support firms through sector-specific

information, training and technical guidance. Such measures would enable manufacturing firms to derive greater productive value from renewable energy consumption and reduce production bottlenecks associated with inefficient energy use.

To mitigate the negative effects associated with transmission-distribution losses, KETRACO and Kenya Power, under the regulatory oversight of EPRA, should implement targeted loss-reduction programmes in areas serving major industrial and commercial loads. These programmes should include rehabilitation and upgrading of ageing transmission-distribution infrastructure, deployment of advanced metering and monitoring technologies, transformer and feeder upgrades and systematic identification of high-loss sections of the network. In parallel, the Ministry of Energy and Petroleum should facilitate the integration of decentralized renewable energy systems, including industrial-scale rooftop solar and embedded generation, particularly in industrial zones where grid constraints are persistent. Reducing technical and non-technical electricity losses would improve the amount and reliability of electricity available to manufacturing firms and strengthen the contribution of renewable energy to industrial production.

5.4.2 Renewable Energy Value Chain Dynamics and the Services Sector

To sustain the immediate benefits of renewable energy installation in the services sector, the Ministry of Energy and Petroleum, in collaboration with EPRA, Kenya Power and county governments, should prioritize the expansion of reliable renewable energy infrastructure in urban and peri-urban service centres. This should include facilitating commercial solar installations, embedded generation, mini-grids and hybrid renewable energy systems for service-oriented enterprises such as ICT hubs, financial institutions, hospitals, educational facilities and other critical service establishments. County governments should incorporate renewable energy infrastructure into local development and urban planning programmes, while EPRA should streamline regulatory and licensing processes for qualifying decentralized energy systems. These measures would help service-sector enterprises maintain reliable electricity access and reduce disruptions to service delivery.

Given the negative lagged effects of renewable energy generation identified in the services-sector analysis, the Ministry of Energy and Petroleum, KETRACO and Kenya Power should prioritize efficient electricity transmission, distribution and system integration alongside renewable energy generation expansion. KETRACO should strengthen transmission infrastructure and grid stability, while Kenya Power should improve distribution networks

serving major service-sector centres and adopt demand-side management and load-monitoring technologies. EPRA should strengthen regulatory monitoring of electricity reliability and quality by requiring electricity distributors to meet established performance standards and by monitoring service interruptions and system losses. These measures would improve the extent to which generated renewable energy is translated into reliable electricity supply for service-sector users.

Since renewable energy consumption demonstrates the strongest positive contribution to services-sector performance, the Ministry of ICT and the Digital Economy, Ministry of Investments, Trade and Industry, EPRA and county governments should promote productive electricity use among service-sector enterprises, particularly small and medium-sized enterprises. Support should focus on improving reliable electricity access for ICT hubs, digital businesses, financial-service providers, health facilities, educational institutions and other energy-dependent service activities. The Ministry of ICT and the Digital Economy should further integrate reliable renewable electricity access into digital infrastructure development programmes, including data centres, digital service hubs and broadband infrastructure. Such measures would enable service-sector firms to expand the adoption of energy-dependent technologies, including digital platforms, data-processing systems, e-commerce and automated service delivery.

To address the adverse effects of transmission-distribution losses, Kenya Power, under the regulatory oversight of EPRA, should implement targeted loss-reduction programmes in major service-sector and commercial centres. These programmes should include upgrading ageing distribution infrastructure, deploying smart meters and network-monitoring technologies, improving transformer and feeder capacity and identifying high-loss sections of the distribution network. The Ministry of Energy and Petroleum should additionally facilitate decentralized renewable energy solutions, including commercial solar systems, battery storage and embedded generation, particularly for critical service facilities where interruptions impose substantial economic and social costs. The Ministry and county governments should facilitate public-private partnerships for the deployment and operation of decentralized energy systems. These interventions would reduce dependence on inefficient transmission-distribution networks, improve electricity reliability and strengthen the capacity of the services sector to contribute to economic growth.

5.4.3 Renewable Energy Value Chain Dynamics and the Agriculture Sector

To manage the short-run disruptions associated with renewable energy installation in agriculture, the Ministry of Energy and Petroleum, in collaboration with the Ministry of Agriculture and Livestock Development and county governments, should promote phased and agriculture-specific deployment of renewable energy infrastructure. Renewable energy projects should be integrated with agricultural activities through irrigation-linked solar systems, agro-processing energy hubs, cold-storage facilities and decentralized mini-grids in rural areas. The Ministry of Agriculture and Livestock Development and county governments should identify priority agricultural value chains and production areas where renewable energy infrastructure can be directly integrated into productive activities. This approach would minimize disruptions associated with the installation phase while ensuring that newly installed capacity contributes directly to agricultural production.

Given the weak role of renewable energy generation in the agricultural-sector model, the Ministry of Energy and Petroleum, Kenya Power and the Rural Electrification and Renewable Energy Corporation (REREC) should prioritize improving energy access and connectivity rather than focusing on generation expansion alone. REREC should accelerate rural electrification and the deployment of appropriate off-grid and decentralized renewable energy systems, while Kenya Power should strengthen last-mile connectivity and distribution networks serving agricultural production and agro-processing centers. The Ministry of Energy and Petroleum should coordinate these interventions to ensure that electricity infrastructure is aligned with agricultural demand centers. This would improve the extent to which available renewable energy translates into reliable electricity access for farmers, agro-processors and other agricultural enterprises.

To strengthen the positive effects of renewable energy consumption, the Ministry of Agriculture and Livestock Development, working with county departments of agriculture, REREC and relevant financial institutions, should promote the adoption of energy-dependent agricultural technologies. Priority should be given to solar-powered irrigation systems, cold-storage facilities, crop-drying equipment, milk-cooling systems, water pumping and other productive technologies appropriate to local agricultural value chains. The Ministry of Agriculture and Livestock Development and county agricultural extension services should provide farmers with technical training on the operation, maintenance and efficient use of renewable energy technologies. Financial institutions and relevant government programmes

should also facilitate affordable financing for farmers and agricultural cooperatives to acquire such technologies. These interventions would increase the productive use of renewable electricity and strengthen its contribution to agricultural output.

Although transmission-distribution losses demonstrate a complex relationship with agricultural output, reducing such losses remains important for improving the efficiency and reliability of electricity supply to rural productive activities. Kenya Power, under the oversight of EPRA, should prioritize upgrading distribution infrastructure in areas with significant agricultural production and agro-processing activities. This should include rehabilitation of ageing distribution lines, transformer upgrades, improved metering and monitoring systems and targeted identification and reduction of high-loss feeders. At the same time, REREC and county governments should facilitate decentralized renewable energy systems in locations where extension of the national grid is technically or economically difficult. Supporting community-based energy systems and farmer cooperatives in managing appropriate localized renewable energy projects would provide alternative sources of reliable energy and reduce excessive dependence on constrained grid infrastructure.

The county governments, working with the Ministry of Agriculture and Livestock Development and the Ministry of Energy and Petroleum, should align renewable energy investments with local agricultural specializations and county development priorities. County governments should identify major agricultural value chains such as irrigation farming, dairy production, grain storage, horticulture and agro-processing and incorporate the corresponding energy requirements into County Integrated Development Plans (CIDPs). Renewable energy investments should therefore be directed toward locations where reliable energy can support specific productive activities, such as irrigation schemes, milk-cooling centers, aggregation centers, cold-storage facilities and agro-processing enterprises. This localized and value-chain-based approach would improve the alignment between renewable energy investment and agricultural production and enhance the effectiveness of the energy transition in promoting agricultural-sector growth.

5.5 Contribution of the Research

5.5.1 Contribution to Academia

This body of knowledge adds to academic knowledge by offering fresh empirical insights on how green energy impacts Kenya’s sectoral performance. While much of the existing literature

tends to focus on the national or aggregate level, this study goes a step further by disaggregating performance across the key sectors, that is, agriculture, manufacturing and services. This approach helps to demonstrate the different ways in which renewable energy affects each sector, something that hasn't been explored in depth by the existing body of knowledge. The use of the ARDL-ECM models also strengthens the academic contribution, as it accommodates mixed levels of stationarity in the data and allows for immediate and extended effects to be captured in a single model. In so doing, this body of knowledge, besides addressing the gap in the Kenyan context, also offers a template that could be replicated in other developing economies facing similar energy and performance challenges as Kenya.

5.5.2 Contribution to Policy

The findings from this study offer timely and practical guidance for policymakers working to improve Kenya's energy systems and sectoral performance and overall productivity. One key component is the strong role played by green energy production and utilization in boosting productivity, particularly within energy-intensive sectors such as manufacturing. By providing sector-specific findings, the study allows decision-makers to tailor interventions rather than adopting a standardized strategy. Institutions such as the Energy Ministry, KPLC, KETRACO and development partners can use this evidence to support more targeted, cost-effective and productive energy investment strategies.

5.5.3 Contribution to Research

This study offers a helpful starting point for future research. It demonstrates how time series techniques like ARDL can be used effectively when variables are integrated at different levels and it also applies rigorous diagnostics to avoid the problem of spurious results. The incorporation of factors like renewable power installation, transmission losses and capital formation helps broaden the scope beyond traditional energy-growth models. The study highlights areas that future researchers can build on, such as county-level studies, incorporating governance indicators or exploring the environmental dimensions of energy and sectoral performance. These gaps create opportunities for interdisciplinary research that brings together economics, climate change, policy and environmental sustainability.

5.5.4 Contribution to Novel Knowledge

This study contributes to novel knowledge by advancing the understanding of the relationship between renewable energy value chain dynamics and productive-sector performance in Kenya through an integrated renewable energy value-chain perspective. Unlike previous studies that

predominantly focus on a single dimension of renewable energy, such as renewable energy consumption, generation or installed capacity, this study simultaneously examines renewable energy installation, generation, consumption and transmission-distribution losses. This approach recognizes that the economic benefits of renewable energy transition depend on the entire process through which renewable energy infrastructure is developed, electricity is generated, delivered and ultimately utilized. By bringing these interconnected dimensions into a single analytical framework, the study provides a more comprehensive understanding of how renewable energy value chain dynamics influence sectoral and overall economic performance.

The study further contributes novel empirical knowledge by moving beyond aggregate economic growth to examine the effects of renewable energy value chain dynamics across Kenya's three major productive sectors, that is, agriculture, manufacturing and services. This sector-specific perspective is important because the productive sectors differ in their energy requirements, production structures, technological characteristics and dependence on reliable electricity supply. The findings demonstrate that the effects of renewable energy dynamics are not uniform across the sectors, with differences in the direction, magnitude, significance and timing of effects. The study therefore reveals sectoral heterogeneity that may be obscured when renewable energy is examined only against aggregate GDP. This provides a more layered understanding of the economic consequences of renewable energy value chain dynamics and extends existing literature from the conventional renewable-energy–economic-growth nexus to a renewable-energy–productive-sector nexus.

Another important contribution of the study is the reconceptualization of transmission-distribution losses from a predominantly technical problem into an economic problem. Transmission-distribution losses are widely viewed within the energy sector primarily as technical inefficiencies associated with electricity infrastructure and system performance. While this technical perspective is important, the findings of this study demonstrate that losses also have significant economic implications because electricity that is lost before reaching productive users represents energy that cannot contribute fully to agricultural, manufacturing and service-sector activity. By empirically linking losses to productive-sector performance, the study demonstrates that renewable energy-system inefficiency can constrain economic performance and therefore constitutes not only an engineering challenge but also a significant economic-development problem. This contribution broadens the conventional understanding of renewable energy value chain dynamics by showing that expanding renewable generation

capacity without addressing the efficiency of transmission-distribution may limit the extent to which the transition translates into productive economic outcomes.

The study also contributes to knowledge by establishing that the relationship between renewable energy value chain dynamics and productive-sector performance is dynamic rather than exclusively contemporaneous. Through the ARDL-ECM framework, the study identifies both short run adjustments and long-run relationships, including effects that emerge with lags. This finding is particularly important because investments in renewable energy infrastructure may require time before their benefits are translated into increased productive capacity and sectoral output. The study therefore demonstrates that the economic consequences of renewable energy value chain dynamics should be evaluated over both the short and long term rather than through instantaneous relationships alone. The findings reinforce the view that renewable energy infrastructure constitutes a productive economic input capable of influencing capital accumulation, productivity and structural transformation.

The study makes an original contribution by integrating the different stages of the renewable energy value chain with sector-specific productive performance in Kenya within a dynamic analytical framework. Its principal novelty lies in bringing together renewable energy installation, generation, consumption and transmission-distribution losses and examining their differentiated effects on agriculture, manufacturing and services. In doing so, the study not only provides new empirical evidence on Kenya's renewable energy value chain dynamics but also advances the understanding of renewable energy-system losses by demonstrating that what is commonly treated as a technical problem can have material consequences for economic performance and productive-sector development. The study therefore provides a stronger foundation for understanding the economic value of an efficient renewable energy value chain and for designing policies that address both renewable energy expansion and the efficient delivery of electricity to productive users.

5.6 Limitations of the Study

One key constraint of this body of knowledge is the reliance on annual time series data at the national level. While the data used were appropriate for long-term trend analysis, they do not capture short-term seasonal variations or micro-level sectoral dynamics. Also, using aggregated data for each of the sectors may hide important differences within the sector, like between large and small firms or between urban and rural areas. A more micro-level dataset, such as a firm-level or county-level panel dataset, could provide a deeper understanding of how

the renewable energy value chain dynamics affect sectoral performance at different scales and in different contexts.

A limitation of this study is that specific renewable energy value chain dynamics were analyzed as an aggregate rather than disaggregated into its specific components. While geothermal and hydro have relatively reliable long-term data, other renewable sources have scanty or incomplete records because much of the energy they generate is not channeled to the national grid. In many cases, firms and industries generate and consume power independently, without systematic accounting of production, consumption or losses. Therefore, apart from knowing the installed capacity of the small-scale installations, there is limited information on actual energy flows from them. This data limitation makes a source-specific study impractical as it would depend on incomplete and potentially unreliable records. Future research could address this gap as more comprehensive and standardized data become available.

Another limitation is found in the range of indicators that were included in the analytical framework. Although the study incorporated both the sustainable and conventional energy dynamics alongside key variables like capital and labour, it did not account for the influence of institutional quality, political stability, effects of acts of God, regulatory efficiency or policy implementation capacity. These non-quantitative factors can significantly shape energy investment outcomes and performance trends, especially in developing economies like Kenya. Their omission means that the models may not fully capture all the determinants of sectoral performance.

The findings of this study are also context-specific and might not necessarily be universally accepted or replicable in other settings. Kenya's renewable energy landscape and endowment, regulatory structure and framework and sectoral characteristics are unique to Kenya and the results observed in this study are likely influenced by these country-specific dynamics. While the framework used here can be adapted and replicated to other settings, care must be taken when applying the findings beyond the Kenyan context. Future comparative studies involving multiple countries or regions would help validate the broader applicability of these results in other jurisdictions.

5.7 Suggestions for Further Research

Future research could exploit more disaggregated data, particularly at the regional, county or firm level. While this study relied on national-level data, county-level analysis could provide more detailed insights into the area-wise distribution of renewable energy access and

performance outcomes across different regions. Firm-level or industry-specific data could also help to reveal cross-sector differences and capture the influence of firm characteristics, such as size, ownership or technology adoption on renewable energy use and output performance.

Future research could examine the source-specific effects of sustainable energy forms on sectoral performance. Currently, apart from geothermal and hydro, data for other sources are limited because much of the energy is generated and consumed on the sites by firms without being systematically recorded. To address this, researchers could work with energy regulators and industrial producers to access primary records and advocate for standardized reporting, enabling more accurate and detailed analysis of each renewable energy source.

Further studies may also consider integrating institutional and governance indicators into the modeling framework. Factors such as political stability, effects of acts of God, goodwill and corruption levels can significantly affect the performance attributable to renewable energy investments, besides their impact on sectoral performance. Including these qualitative aspects could enrich our understanding of the enabling environment required for renewable energy adoption to translate into measurable sectoral performance gains.

Another important area that calls for further research is the extension of the current framework to other developing countries or through comparative regional analysis. A multi-country approach could help assess whether the relationships observed in Kenya hold across different political, economic and infrastructural contexts. This would also contribute to a better understanding of regional energy policy coordination and integration efforts within East Africa or the broader Sub-Saharan region.

As energy systems evolve, future studies could also explore the environmental and climate dimensions of the renewable energy–sectoral growth nexus. Incorporating variables such as carbon emissions, climate resilience indicators or renewable energy financing and pricing mechanisms would allow researchers to assess not only the economic outcomes but also the environmental sustainability of energy transitions. This would support the formulation of policies that seek to harmonize sectoral development and ecological sustainability in Kenya and economies at the same level of growth and renewable energy resource endowment as Kenya.

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APPENDICES

Appendix A: Political Map of Kenya (Study Area)



(Source; Nations Online Project, n.d.)

Appendix B: School of Graduate Studies (SGS) Approval

MASENO UNIVERSITY
SCHOOL OF GRADUATE STUDIES

Office of the Dean

Our Ref: PHD/ BE/00082/2022

Private Bag, MASENO, KENYA
Tel:(057)351 22/351008/351011
FAX: 254-057-351153/351221
Email: sgs@maseno.ac.ke

Date: 9th March, 2025

TO WHOM IT MAY CONCERN

RE: PROPOSAL APPROVAL FOR MASIBAYI PETER SITUMA— PHD/BE/00082/2022

The above named is registered in the programme of Doctor of Philosophy in Economics in the School of Business and Economics, Maseno University. This is to confirm that his research proposal titled "**Influence of Renewable Energy Production-Consumption Dynamics on Sectoral Growth in Kenya**" has been approved for conduct of research subject to obtaining all other permissions/clearances that may be required beforehand.

DEAN SCHOOL OF GRADUATE STUDIES MASENO UNIVERSITY 14 MAR 2025 P.O. Box PRIVATE

Dr. P. O. Onyango
DEAN, SCHOOL OF GRADUATE STUDIES

Appendix C: Maseno University Scientific and Ethics Review Committee (MUSERC) Approval

MASENO UNIVERSITYSCIENTIFIC AND ETHICS REVIEW COMMITTEE

Tel: +254 057 351 622 Ext: 3050
Fax: +254 057 351 221

Private Bag – 40105, Maseno, Kenya
Email: muerc-secretariate@maseno.ac.ke

REF: MSU/DRPI/MUSERC/01482/25 **Date:** 7th May, 2025

TO: Masibayi Peter Situma
PHD/BE/00082/022
Department of Economics
School of Business and Economics
Maseno University
P. O. Box, Private Bag, Maseno, Kenya

Dear Sir,

Re: Influence of Renewable Energy Production-Consumption Dynamics on Sectoral Growth in Kenya

This is to inform you that **Maseno University Scientific and Ethics Review Committee (MUSERC)** has reviewed and approved your above research proposal. Your application approval number is MUSERC/01482/25.The approval period is 7th May, 2025 – 6th May, 2026.

This approval is subject to compliance with the following requirements;

i. Only approved documents including (informed consents, study instruments, MTA) will be used.
ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by Maseno University Scientific and Ethics Review Committee (MUSERC).
iii. Death and life threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to Maseno University Scientific and Ethics Review Committee (MUSERC) within 24 hours of notification.
iv. Any changes, anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to Maseno University Scientific and Ethics Review Committee (MUSERC) within 24 hours.
v. Clearance for export of biological specimens must be obtained from relevant institutions.
vi. Submission of a request for renewal of approval at least 60 days prior to expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days upon completion of the study to Maseno University Scientific and Ethics Review Committee (MUSERC).

Prior to commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology and Innovation (NACOSTI) https://oris.nacosti.go.ke and also obtain other clearances needed.

Yours sincerely

Dr. Bonuke Anyona, PhD
Chairman, MUSERC

MASENO UNIVERSITY ETHICS REVIEW COMMITTEE 07 MAY 2025

MASENO UNIVERSITY IS ISO 9001 CERTIFIED

Appendix D: NACOSTI Approval

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: **745638**

Date of Issue: **23/May/2025**

RESEARCH LICENSE



This is to Certify that Mr.. Peter Situma Masibayi of Maseno University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Kisumu on the topic: Influence of Renewable Energy Production -consumption Dynamics on sectoral growth in Kenya for the period ending : 23/May/2026.

License No: **NACOSTI/P/25/4174484**

745638

Applicant Identification Number

Deputy Director
NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Verification QR Code

NOTE: This is a computer generated License. To verify the authenticity of this document, Scan the QR Code using QR scanner application.

See overleaf for conditions

Appendix E: Raw Data

Year	AVA(billions)	MVA(billions)	SVA(billions)	L(millions)	REG(000)	RET(000)	RNTL(000)	GCF(billions)	REC(000)
1980	593.46	227.14	394.53	1,190.80	108.00	313.50	249.00	388.98	6.00
1981	628.62	235.28	403.98	1,243.70	138.10	368.50	285.40	410.01	7.00
1982	674.93	240.58	413.53	1,280.90	139.70	383.50	315.00	425.50	7.23
1983	687.45	251.42	424.88	1,339.40	174.00	384.50	324.00	410.38	8.00
1984	663.55	262.26	442.33	1,385.40	172.40	385.50	304.00	395.43	8.32
1985	690.19	274.04	461.78	1,462.00	201.60	398.50	337.00	415.27	9.00
1986	724.17	289.93	487.23	1,536.90	210.50	398.60	314.00	506.01	10.58
1987	754.52	306.52	515.68	1,624.30	218.70	398.70	404.00	535.79	11.00
1988	788.88	324.91	545.12	1,736.20	264.60	398.80	507.00	592.82	12.00
1989	821.33	344.09	574.57	1,796.20	279.10	542.50	482.00	590.61	12.32
1990	849.85	362.10	606.02	1,894.20	527.00	542.60	479.80	653.01	13.00
1991	843.81	375.85	628.47	2,557.10	504.00	648.50	507.00	610.49	13.30
1992	815.74	380.36	647.92	2,753.40	486.00	648.60	540.00	527.68	13.54
1993	789.05	387.21	663.74	2,997.60	492.00	648.70	595.00	540.92	14.00
1994	813.34	394.57	686.82	3,356.20	383.00	648.80	598.00	618.60	14.26
1995	852.31	409.95	726.27	3,656.60	512.00	648.90	643.00	731.84	14.56
1996	890.42	424.99	755.72	4,325.80	515.00	644.50	712.00	570.57	14.78
1997	863.13	424.82	815.17	4,698.40	488.00	648.50	739.00	551.03	14.83
1998	934.68	415.83	834.61	5,096.70	512.00	639.50	865.00	579.79	14.97
1999	1,000.97	406.19	914.06	5,492.60	505.00	640.00	896.60	589.99	15.12
2000	988.19	408.95	973.51	5,911.60	543.00	731.50	957.00	636.06	15.37
2001	1,103.39	410.15	1,069.62	6,409.80	574.20	735.20	889.00	717.10	15.43
2002	1,064.81	410.48	1,412.41	6,866.80	666.69	735.70	936.00	684.69	17.00
2003	1,090.69	435.00	1,831.86	7,325.70	728.43	735.50	949.00	647.58	19.00
2004	1,109.76	454.41	2,151.31	7,998.50	900.15	805.30	946.00	698.73	18.76
2005	1,186.40	475.59	2,387.20	8,505.00	1,032.94	805.40	968.00	851.04	18.24
2006	1,206.93	514.63	2,521.50	8,993.40	1,079.70	805.60	968.10	941.28	19.00
2007	1,268.36	537.15	2,706.25	9,478.90	1,089.49	805.35	1,096.00	1,033.74	19.67
2008	1,205.15	543.29	2,782.26	9,953.80	1,177.14	847.00	1,062.00	979.06	19.23
2009	1,177.46	537.57	2,960.44	10,456.50	1,862.19	888.00	1,057.00	980.42	19.58
2010	1,299.33	567.44	3,176.46	10,955.10	1,266.65	917.00	1,068.00	1,207.78	21.98
2011	1,330.20	611.34	3,329.98	12,116.20	2,053.79	925.60	1,180.00	1,261.20	21.86
2012	1,362.78	613.59	3,478.04	12,781.10	1,816.17	969.50	1,329.00	1,374.63	24.76
2013	1,417.98	644.16	3,585.91	13,517.00	1,963.00	1,003.20	1,507.00	1,374.01	25.28
2014	1,437.54	656.26	3,802.33	14,355.80	3,687.11	1,144.80	2,079.00	1,658.12	27.00
2015	1,500.58	694.70	4,048.98	15,203.10	4,874.83	1,474.10	1,624.00	1,609.78	33.00
2016	1,521.43	707.88	4,286.58	16,032.80	4,612.48	1,497.40	1,905.10	1,472.62	33.46
2017	1,501.82	712.81	4,506.03	16,942.70	5,662.35	1,505.00	1,932.20	1,568.88	35.88
2018	1,587.78	738.31	4,778.61	17,783.20	4,980.24	1,876.00	2,243.80	1,591.03	34.12
2019	1,630.61	757.79	5,098.97	18,142.70	6,223.00	2,041.70	2,723.60	1,660.45	36.22
2020	1,705.99	755.61	5,005.50	17,406.70	5,485.02	2,085.70	2,689.00	1,687.37	39.32
2021	1,699.96	810.83	5,486.09	18,331.60	5,988.45	2,311.80	2,898.00	1,849.71	40.60
2022	1,675.05	831.90	5,849.14	19,148.20	6,491.88	3,119.40	2,839.00	1,833.10	41.29
2023	1,784.78	849.80	6,244.36	19,996.30	6,995.31	3,041.70	3,057.00	1,819.06	41.66
2024	1,867.49	873.83	6,639.58	20,844.40	7,498.74	3,033.60	2,990.90	1,913.16	42.04

Appendix F: Correlation Analysis with Raw Data, Manufacturing

Date: 03/17/26 Time: 14:14
Sample: 1980 2024
Included observations: 45

Correlation t-Statistic Probability	MVA	RET	REG	REC	RNTL	GCF	L
MVA	1.000000						

RET	0.910797	1.000000					
	14.46630	-----					
	0.0000	-----					
REG	0.929127	0.955242	1.000000				
	16.47736	21.17433	-----				
	0.0000	0.0000	-----				
REC	0.982902	0.942604	0.966709	1.000000			
	35.00450	18.51106	24.77383	-----			
	0.0000	0.0000	0.0000	-----			
RNTL	0.960314	0.958686	0.965301	0.978679	1.000000		
	22.57710	22.09950	24.23934	31.24481	-----		
	0.0000	0.0000	0.0000	0.0000	-----		
GCF	0.977984	0.892657	0.940020	0.969365	0.952072	1.000000	
	30.73185	12.98660	18.07021	25.87926	20.41080	-----	
	0.0000	0.0000	0.0000	0.0000	0.0000	-----	
L	0.985969	0.897571	0.932655	0.975657	0.960281	0.976646	1.000000
	38.73134	13.35032	16.95223	29.17372	22.56697	29.80751	-----
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-----

Appendix G: Correlation Analysis with Raw Data, Services

Date: 03/17/26 Time: 14:16
Sample: 1980 2024
Included observations: 45

Correlation t-Statistic Probability	SVA	RET	REG	REC	GCF	L
SVA	1.000000					

RET	0.923924	1.000000				
	15.83622	-----				
	0.0000	-----				
REG	0.947639	0.955242	1.000000			
	19.45899	21.17433	-----			
	0.0000	0.0000	-----			
REC	0.972414	0.942604	0.966709	1.000000		
	27.33628	18.51106	24.77383	-----		
	0.0000	0.0000	0.0000	-----		
GCF	0.978049	0.892657	0.940020	0.969365	1.000000	
	30.77872	12.98660	18.07021	25.87926	-----	
	0.0000	0.0000	0.0000	0.0000	-----	
L	0.988397	0.897571	0.932655	0.975657	0.976646	1.000000
	42.67000	13.35032	16.95223	29.17372	29.80751	-----
	0.0000	0.0000	0.0000	0.0000	0.0000	-----

Appendix H: Correlation Analysis with Raw Data, Agriculture

Date: 03/17/26 Time: 14:15
Sample: 1980 2024
Included observations: 45

Correlation t-Statistic Probability	AVA	RET	REG	REC	GCF	L
AVA	1.000000					

RET	0.889808	1.000000				
	12.78638	-----				
	0.0000	-----				
REG	0.910333	0.955242	1.000000			
	14.42329	21.17433	-----			
	0.0000	0.0000	-----			
REC	0.971932	0.942604	0.966709	1.000000		
	27.09042	18.51106	24.77383	-----		
	0.0000	0.0000	0.0000	-----		
GCF	0.970755	0.892657	0.940020	0.969365	1.000000	
	26.51559	12.98660	18.07021	25.87926	-----	
	0.0000	0.0000	0.0000	0.0000	-----	
L	0.990090	0.897571	0.932655	0.975657	0.976646	1.000000
	46.23183	13.35032	16.95223	29.17372	29.80751	-----
	0.0000	0.0000	0.0000	0.0000	0.0000	-----

Appendix I: Model Selection Criteria for the Manufacturing Sector

Model Selection Criteria Table
Dependent Variable: MVA
Date: 03/17/26 Time: 15:34
Sample: 1981 2024
Included observations: 40

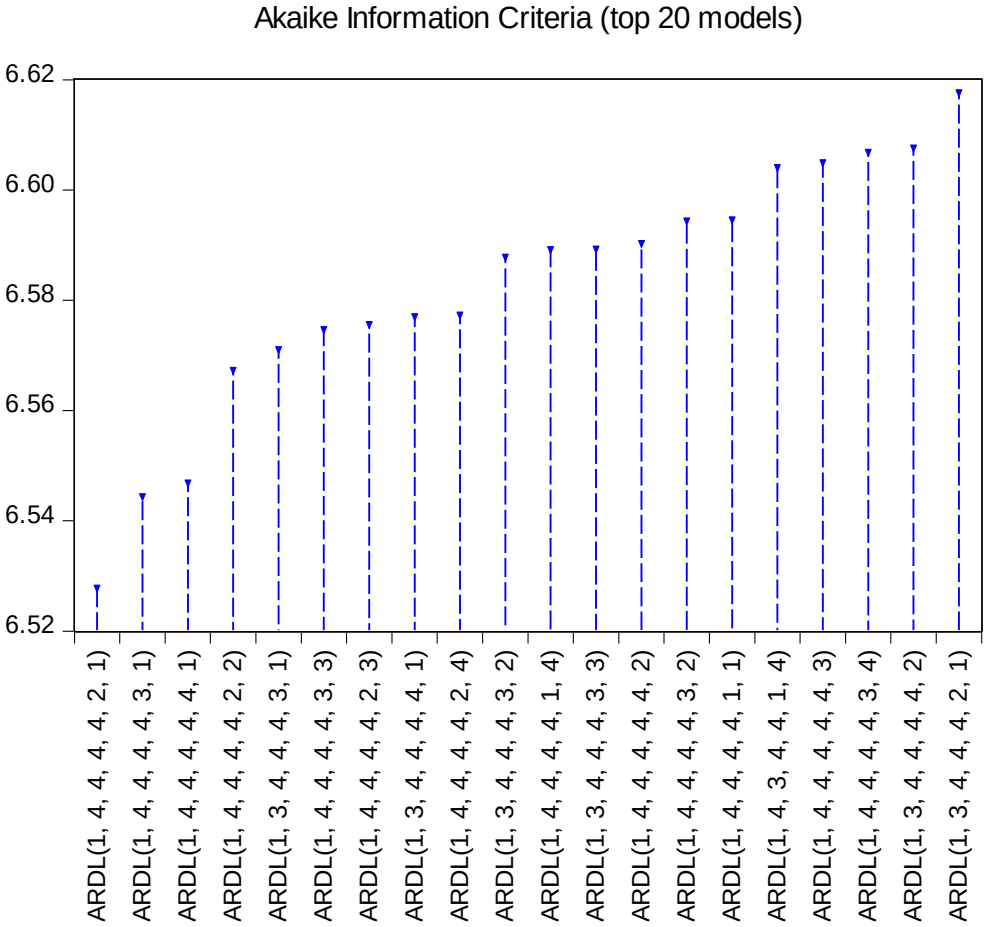
Model	LogL	AIC*	BIC	HQ	Adj. R-sq	Specification
14	-103.555933	6.527797	7.667790	6.939982	0.841072	ARDL(1, 4, 4, 4, 4, 2, 1)
9	-102.888003	6.544400	7.726616	6.971852	0.833483	ARDL(1, 4, 4, 4, 4, 3, 1)
4	-101.937227	6.546861	7.771299	6.989579	0.826779	ARDL(1, 4, 4, 4, 4, 4, 1)
13	-103.346097	6.567305	7.749520	6.994757	0.829625	ARDL(1, 4, 4, 4, 4, 2, 2)
3134	-104.421381	6.571069	7.711063	6.983255	0.834044	ARDL(1, 3, 4, 4, 4, 3, 1)
7	-101.494054	6.574703	7.841362	7.032687	0.813632	ARDL(1, 4, 4, 4, 4, 3, 3)
12	-102.512307	6.575615	7.800053	7.018333	0.821726	ARDL(1, 4, 4, 4, 4, 2, 3)
3129	-103.540174	6.577009	7.759224	7.004461	0.827964	ARDL(1, 3, 4, 4, 4, 4, 1)
11	-101.546343	6.577317	7.843977	7.035301	0.813144	ARDL(1, 4, 4, 4, 4, 2, 4)
3133	-103.756227	6.587811	7.770027	7.015263	0.826095	ARDL(1, 3, 4, 4, 4, 3, 2)
16	-102.783309	6.589165	7.813603	7.031883	0.819293	ARDL(1, 4, 4, 4, 4, 1, 4)
3132	-102.785300	6.589265	7.813703	7.031983	0.819275	ARDL(1, 3, 4, 4, 4, 3, 3)
3	-101.806047	6.590302	7.856962	7.048286	0.810702	ARDL(1, 4, 4, 4, 4, 4, 2)
8	-102.887449	6.594372	7.818810	7.037090	0.818350	ARDL(1, 4, 4, 4, 4, 3, 2)
19	-105.891759	6.594588	7.692360	6.991507	0.834142	ARDL(1, 4, 4, 4, 4, 1, 1)
641	-104.081407	6.604070	7.786286	7.031522	0.823244	ARDL(1, 4, 3, 4, 4, 1, 4)
2	-101.098881	6.604944	7.913826	7.078194	0.796976	ARDL(1, 4, 4, 4, 4, 4, 3)
6	-101.137333	6.606867	7.915748	7.080117	0.796585	ARDL(1, 4, 4, 4, 4, 3, 4)
3128	-103.152825	6.607641	7.832079	7.050359	0.815924	ARDL(1, 3, 4, 4, 4, 4, 2)
3139	-106.353151	6.617658	7.715429	7.014577	0.830271	ARDL(1, 3, 4, 4, 4, 2, 1)
636	-103.441975	6.622099	7.846536	7.064817	0.813243	ARDL(1, 4, 3, 4, 4, 2, 4)
3131	-102.611268	6.630563	7.897223	7.088548	0.802925	ARDL(1, 3, 4, 4, 4, 3, 4)
1	-100.623116	6.631156	7.982259	7.119672	0.776967	ARDL(1, 4, 4, 4, 4, 4, 4)
3127	-102.624432	6.631222	7.897881	7.089206	0.802796	ARDL(1, 3, 4, 4, 4, 4, 3)
17	-104.684823	6.634241	7.816457	7.061693	0.817830	ARDL(1, 4, 4, 4, 4, 1, 3)
632	-103.726517	6.636326	7.860763	7.079044	0.810567	ARDL(1, 4, 3, 4, 4, 3, 3)
18	-105.864996	6.643250	7.783243	7.055435	0.821622	ARDL(1, 4, 4, 4, 4, 1, 2)
631	-102.878236	6.643912	7.910571	7.101896	0.800277	ARDL(1, 4, 3, 4, 4, 3, 4)
3757	-105.097661	6.654883	7.837099	7.082335	0.814031	ARDL(1, 3, 3, 4, 4, 3, 3)
3138	-106.122638	6.656132	7.796126	7.068318	0.819309	ARDL(1, 3, 4, 4, 4, 2, 2)
634	-106.168807	6.658440	7.798434	7.070626	0.818892	ARDL(1, 4, 3, 4, 4, 3, 1)
629	-105.279052	6.663953	7.846168	7.091404	0.812337	ARDL(1, 4, 3, 4, 4, 4, 1)
3126	-102.434156	6.671708	7.980589	7.144958	0.782959	ARDL(1, 3, 4, 4, 4, 4, 4)
3144	-108.485768	6.674288	7.729838	7.055942	0.823761	ARDL(1, 3, 4, 4, 4, 1, 1)
626	-102.514160	6.675708	7.984590	7.148958	0.782089	ARDL(1, 4, 3, 4, 4, 4, 4)
627	-103.524003	6.676200	7.942860	7.134184	0.793723	ARDL(1, 4, 3, 4, 4, 4, 3)
639	-107.532811	6.676641	7.774412	7.073560	0.819958	ARDL(1, 4, 3, 4, 4, 2, 1)
637	-105.562926	6.678146	7.860362	7.105598	0.809654	ARDL(1, 4, 3, 4, 4, 2, 3)
3759	-107.589903	6.679495	7.777267	7.076415	0.819444	ARDL(1, 3, 3, 4, 4, 3, 1)
3754	-106.758777	6.687939	7.827932	7.100125	0.813470	ARDL(1, 3, 3, 4, 4, 4, 1)
2513	-109.909112	6.695456	7.708783	7.061843	0.822589	ARDL(1, 4, 0, 4, 4, 2, 2)
3758	-106.975282	6.698764	7.838758	7.110950	0.811439	ARDL(1, 3, 3, 4, 4, 3, 2)
644	-108.979731	6.698987	7.754536	7.080640	0.819354	ARDL(1, 4, 3, 4, 4, 1, 1)
642	-106.994550	6.699728	7.839721	7.111913	0.811258	ARDL(1, 4, 3, 4, 4, 1, 3)
3143	-108.023116	6.701156	7.798927	7.098075	0.815490	ARDL(1, 3, 4, 4, 4, 1, 2)
3752	-105.049967	6.702498	7.926936	7.145216	0.797608	ARDL(1, 3, 3, 4, 4, 4, 3)
3756	-105.058949	6.702947	7.927385	7.145665	0.797517	ARDL(1, 3, 3, 4, 4, 3, 4)

3137	-106.102333	6.705117	7.887332	7.132568	0.804450	ARDL(1, 3, 4, 4, 4, 2, 3)
638	-107.102828	6.705141	7.845135	7.117327	0.810233	ARDL(1, 4, 3, 4, 4, 2, 2)
628	-105.154716	6.707736	7.932173	7.150454	0.796545	ARDL(1, 4, 3, 4, 4, 4, 2)
633	-106.168166	6.708408	7.890624	7.135860	0.803806	ARDL(1, 4, 3, 4, 4, 3, 2)
3753	-106.404682	6.720234	7.902450	7.147686	0.801472	ARDL(1, 3, 3, 4, 4, 4, 2)
2518	-111.648808	6.732440	7.703546	7.083562	0.817850	ARDL(1, 4, 0, 4, 4, 1, 2)
2508	-109.722734	6.736137	7.791686	7.117790	0.812517	ARDL(1, 4, 0, 4, 4, 3, 2)
643	-108.823082	6.741154	7.838926	7.138074	0.807961	ARDL(1, 4, 3, 4, 4, 1, 2)
3136	-105.883465	6.744173	7.968611	7.186891	0.788995	ARDL(1, 3, 4, 4, 4, 2, 4)
3142	-107.893425	6.744671	7.884665	7.156857	0.802581	ARDL(1, 3, 4, 4, 4, 1, 3)
1888	-109.896366	6.744818	7.800368	7.126472	0.810882	ARDL(1, 4, 1, 4, 4, 2, 2)
2512	-109.909034	6.745452	7.801001	7.127105	0.810762	ARDL(1, 4, 0, 4, 4, 2, 3)
2503	-108.941388	6.747069	7.844841	7.143989	0.806821	ARDL(1, 4, 0, 4, 4, 4, 2)
3751	-105.008731	6.750437	8.017096	7.208421	0.777827	ARDL(1, 3, 3, 4, 4, 4, 4)
2509	-111.075526	6.753776	7.767104	7.120164	0.811934	ARDL(1, 4, 0, 4, 4, 3, 1)
2753	-111.175211	6.758761	7.772088	7.125148	0.810995	ARDL(1, 4, 0, 2, 4, 4, 2)
2511	-109.392234	6.769612	7.867383	7.166531	0.802417	ARDL(1, 4, 0, 4, 4, 2, 4)
1263	-109.448098	6.772405	7.870177	7.169324	0.801864	ARDL(1, 4, 2, 4, 4, 2, 2)
2517	-111.596902	6.779845	7.793173	7.146232	0.806967	ARDL(1, 4, 0, 4, 4, 1, 3)
2514	-112.618454	6.780923	7.752028	7.132044	0.808801	ARDL(1, 4, 0, 4, 4, 2, 1)
2763	-113.628866	6.781443	7.710327	7.117298	0.810066	ARDL(1, 4, 0, 2, 4, 2, 2)
1893	-111.631955	6.781598	7.794925	7.147985	0.806628	ARDL(1, 4, 1, 4, 4, 1, 2)
2516	-110.633171	6.781659	7.837208	7.163312	0.803785	ARDL(1, 4, 0, 4, 4, 1, 4)
2519	-113.669414	6.783471	7.712354	7.119326	0.809681	ARDL(1, 4, 0, 4, 4, 1, 1)
1883	-109.686907	6.784345	7.882117	7.181265	0.799484	ARDL(1, 4, 1, 4, 4, 3, 2)
3764	-110.696018	6.784801	7.840351	7.166454	0.803167	ARDL(1, 3, 3, 4, 4, 2, 1)
5634	-112.710697	6.785535	7.756641	7.136656	0.807917	ARDL(1, 3, 0, 4, 4, 3, 1)
2507	-109.722053	6.786103	7.883874	7.183022	0.799132	ARDL(1, 4, 0, 4, 4, 3, 3)
2751	-109.854434	6.792722	7.890493	7.189641	0.797798	ARDL(1, 4, 0, 2, 4, 4, 4)
3141	-107.887503	6.794375	7.976591	7.221827	0.786193	ARDL(1, 3, 4, 4, 4, 1, 4)
1887	-109.888117	6.794406	7.892178	7.191325	0.797457	ARDL(1, 4, 1, 4, 4, 2, 3)
2502	-108.916372	6.795819	7.935812	7.208004	0.792221	ARDL(1, 4, 0, 4, 4, 4, 3)
1878	-108.941179	6.797059	7.937053	7.209245	0.791963	ARDL(1, 4, 1, 4, 4, 4, 2)
3769	-111.954996	6.797750	7.811077	7.164137	0.803480	ARDL(1, 3, 3, 4, 4, 1, 1)
1886	-108.957247	6.797862	7.937856	7.210048	0.791796	ARDL(1, 4, 1, 4, 4, 2, 4)
2504	-110.978290	6.798914	7.854464	7.180568	0.800369	ARDL(1, 4, 0, 4, 4, 4, 1)
2501	-107.980159	6.799008	7.981224	7.226460	0.785200	ARDL(1, 4, 0, 4, 4, 4, 4)
1884	-111.074234	6.803712	7.859261	7.185365	0.799409	ARDL(1, 4, 1, 4, 4, 3, 1)
2628	-111.149010	6.807451	7.863000	7.189104	0.798658	ARDL(1, 4, 0, 3, 4, 4, 2)
2128	-111.159442	6.807972	7.863522	7.189626	0.798553	ARDL(1, 4, 1, 2, 4, 4, 2)
2752	-111.160156	6.808008	7.863557	7.189661	0.798546	ARDL(1, 4, 0, 2, 4, 4, 3)
1891	-110.169737	6.808487	7.906258	7.205406	0.794585	ARDL(1, 4, 1, 4, 4, 1, 4)
1268	-111.173731	6.808687	7.864236	7.190340	0.798409	ARDL(1, 4, 2, 4, 4, 1, 2)
876	-107.190176	6.809509	8.033946	7.252227	0.774748	ARDL(1, 4, 3, 2, 4, 4, 4)
1264	-111.271191	6.813560	7.869109	7.195213	0.797424	ARDL(1, 4, 2, 4, 4, 2, 1)
1258	-109.307384	6.815369	7.955363	7.227555	0.788119	ARDL(1, 4, 2, 4, 4, 3, 2)
1269	-112.359454	6.817973	7.831300	7.184360	0.799465	ARDL(1, 4, 2, 4, 4, 1, 1)
1259	-110.366187	6.818309	7.916081	7.215229	0.792557	ARDL(1, 4, 2, 4, 4, 3, 1)
2506	-109.386663	6.819333	7.959327	7.231519	0.787278	ARDL(1, 4, 0, 4, 4, 3, 4)
2762	-113.393952	6.819698	7.790803	7.170819	0.801242	ARDL(1, 4, 0, 2, 4, 2, 3)
1253	-108.397410	6.819871	8.002086	7.247322	0.780672	ARDL(1, 4, 2, 4, 4, 4, 2)
2638	-113.404336	6.820217	7.791322	7.171338	0.801139	ARDL(1, 4, 0, 3, 4, 2, 2)
1262	-109.425271	6.821264	7.961257	7.233449	0.786867	ARDL(1, 4, 2, 4, 4, 2, 3)
1894	-113.476077	6.823804	7.794910	7.174925	0.800424	ARDL(1, 4, 1, 4, 4, 1, 1)
1889	-112.524992	6.826250	7.839577	7.192637	0.797798	ARDL(1, 4, 1, 4, 4, 2, 1)
2126	-109.555134	6.827757	7.967750	7.239942	0.785478	ARDL(1, 4, 1, 2, 4, 4, 4)
3763	-110.569322	6.828466	7.926238	7.225386	0.790439	ARDL(1, 3, 3, 4, 4, 2, 2)

646	-109.587707	6.829385	7.969379	7.241571	0.785128	ARDL(1, 4, 3, 4, 4, 0, 4)
5629	-112.588901	6.829445	7.842773	7.195832	0.797151	ARDL(1, 3, 0, 4, 4, 4, 1)
1892	-111.596867	6.829843	7.885393	7.211497	0.794099	ARDL(1, 4, 1, 4, 4, 1, 3)
2138	-113.603019	6.830151	7.801257	7.181272	0.799153	ARDL(1, 4, 1, 2, 4, 2, 2)
2758	-113.624526	6.831226	7.802332	7.182347	0.798937	ARDL(1, 4, 0, 2, 4, 3, 2)
1882	-109.676702	6.833835	7.973829	7.246021	0.784170	ARDL(1, 4, 1, 4, 4, 3, 3)
3768	-111.680532	6.834027	7.889576	7.215680	0.793235	ARDL(1, 3, 3, 4, 4, 1, 2)
886	-109.688554	6.834428	7.974421	7.246613	0.784042	ARDL(1, 4, 3, 2, 4, 2, 4)
5009	-112.703479	6.835174	7.848502	7.201561	0.795986	ARDL(1, 3, 1, 4, 4, 3, 1)
5633	-112.710595	6.835530	7.848857	7.201917	0.795913	ARDL(1, 3, 0, 4, 4, 3, 2)
766	-109.710753	6.835538	7.975531	7.247723	0.783802	ARDL(1, 4, 3, 3, 4, 1, 4)
891	-110.715141	6.835757	7.933529	7.232677	0.788906	ARDL(1, 4, 3, 2, 4, 1, 4)
1876	-107.785225	6.839261	8.063699	7.281979	0.767946	ARDL(1, 4, 1, 4, 4, 4, 4)
2626	-109.827744	6.841387	7.981381	7.253573	0.782534	ARDL(1, 4, 0, 3, 4, 4, 4)
1503	-110.843616	6.842181	7.939952	7.239100	0.787546	ARDL(1, 4, 2, 2, 4, 4, 2)
1877	-108.904833	6.845242	8.027457	7.272693	0.775036	ARDL(1, 4, 1, 4, 4, 4, 3)
251	-106.917877	6.845894	8.112553	7.303878	0.755574	ARDL(1, 4, 4, 2, 4, 4, 4)
2643	-114.921980	6.846099	7.774983	7.181954	0.797380	ARDL(1, 4, 0, 3, 4, 1, 2)
1261	-108.934203	6.846710	8.028926	7.274162	0.774706	ARDL(1, 4, 2, 4, 4, 2, 4)
1881	-108.954681	6.847734	8.029950	7.275186	0.774475	ARDL(1, 4, 1, 4, 4, 3, 4)
1879	-110.976862	6.848843	7.946615	7.245763	0.786125	ARDL(1, 4, 1, 4, 4, 4, 1)
2768	-116.001663	6.850083	7.736745	7.170672	0.797397	ARDL(1, 4, 0, 2, 4, 1, 2)
878	-110.090507	6.854525	7.994519	7.266711	0.779658	ARDL(1, 4, 3, 2, 4, 4, 2)
2761	-113.104213	6.855211	7.868538	7.221598	0.791857	ARDL(1, 4, 0, 2, 4, 2, 4)
1267	-111.112187	6.855609	7.953381	7.252529	0.784673	ARDL(1, 4, 2, 4, 4, 1, 3)
751	-107.117421	6.855871	8.122531	7.313855	0.753123	ARDL(1, 4, 3, 3, 4, 4, 4)
1254	-110.125383	6.856269	7.996263	7.268455	0.779274	ARDL(1, 4, 2, 4, 4, 4, 1)
2137	-113.130059	6.856503	7.869831	7.222890	0.791588	ARDL(1, 4, 1, 2, 4, 2, 3)
2003	-111.134381	6.856719	7.954491	7.253639	0.784434	ARDL(1, 4, 1, 3, 4, 4, 2)
2627	-111.136073	6.856804	7.954575	7.253723	0.784416	ARDL(1, 4, 0, 3, 4, 4, 3)
2127	-111.156255	6.857813	7.955584	7.254732	0.784198	ARDL(1, 4, 1, 2, 4, 4, 3)
2136	-112.162042	6.858102	7.913652	7.239756	0.788197	ARDL(1, 4, 1, 2, 4, 2, 4)
1266	-110.169318	6.858466	7.998460	7.270652	0.778788	ARDL(1, 4, 2, 4, 4, 1, 4)
2637	-113.210274	6.860514	7.873841	7.226901	0.790750	ARDL(1, 4, 0, 3, 4, 2, 3)
761	-109.224371	6.861219	8.043434	7.288670	0.771413	ARDL(1, 4, 3, 3, 4, 2, 4)
253	-109.235407	6.861770	8.043986	7.289222	0.771287	ARDL(1, 4, 4, 2, 4, 4, 2)
1257	-109.283294	6.864165	8.046380	7.291617	0.770739	ARDL(1, 4, 2, 4, 4, 3, 3)
1252	-108.372941	6.868647	8.093085	7.311365	0.761026	ARDL(1, 4, 2, 4, 4, 4, 3)
3767	-111.375331	6.868767	7.966538	7.265686	0.781822	ARDL(1, 3, 3, 4, 4, 1, 3)
2767	-115.379614	6.868981	7.797864	7.204836	0.792690	ARDL(1, 4, 0, 2, 4, 1, 3)
2013	-113.383297	6.869165	7.882493	7.235552	0.788932	ARDL(1, 4, 1, 3, 4, 2, 2)
2757	-113.388944	6.869447	7.882775	7.235834	0.788872	ARDL(1, 4, 0, 2, 4, 3, 3)
3762	-110.403033	6.870152	8.010145	7.282337	0.776188	ARDL(1, 3, 3, 4, 4, 2, 3)
2633	-113.404291	6.870215	7.883542	7.236602	0.788710	ARDL(1, 4, 0, 3, 4, 3, 2)
2141	-113.421529	6.871076	7.884404	7.237464	0.788528	ARDL(1, 4, 1, 2, 4, 1, 4)
877	-109.474072	6.873704	8.055919	7.301155	0.768541	ARDL(1, 4, 3, 2, 4, 4, 3)
5632	-112.474691	6.873735	7.929284	7.255388	0.784860	ARDL(1, 3, 0, 4, 4, 3, 3)
1513	-113.481832	6.874092	7.887419	7.240479	0.787890	ARDL(1, 4, 2, 2, 4, 2, 2)
2001	-109.489417	6.874471	8.056686	7.301923	0.768364	ARDL(1, 4, 1, 3, 4, 4, 4)
1501	-109.492380	6.874619	8.056835	7.302071	0.768329	ARDL(1, 4, 2, 2, 4, 4, 4)
21	-109.528850	6.876442	8.058658	7.303894	0.767907	ARDL(1, 4, 4, 4, 4, 0, 4)
2642	-114.534084	6.876704	7.847810	7.227825	0.789582	ARDL(1, 4, 0, 3, 4, 1, 3)
2521	-113.542582	6.877129	7.890457	7.243516	0.787244	ARDL(1, 4, 0, 4, 4, 0, 4)
881	-109.556559	6.877828	8.060044	7.305280	0.767585	ARDL(1, 4, 3, 2, 4, 3, 4)
2766	-114.557620	6.877881	7.848987	7.229002	0.789334	ARDL(1, 4, 0, 2, 4, 1, 4)
5004	-112.560185	6.878009	7.933559	7.259663	0.783938	ARDL(1, 3, 1, 4, 4, 4, 1)
5628	-112.576594	6.878830	7.934379	7.260483	0.783761	ARDL(1, 3, 0, 4, 4, 4, 2)

2133	-113.601525	6.880076	7.893404	7.246464	0.786616	ARDL(1, 4, 1, 2, 4, 3, 2)
2644	-116.612021	6.880601	7.767263	7.201190	0.791119	ARDL(1, 4, 0, 3, 4, 1, 1)
887	-111.638628	6.881931	7.979703	7.278851	0.778930	ARDL(1, 4, 3, 2, 4, 2, 3)
266	-110.649455	6.882473	8.022466	7.294658	0.773413	ARDL(1, 4, 4, 2, 4, 1, 4)
2639	-115.667201	6.883360	7.812244	7.219215	0.789688	ARDL(1, 4, 0, 3, 4, 2, 1)
261	-109.686738	6.884337	8.066552	7.311789	0.766067	ARDL(1, 4, 4, 2, 4, 2, 4)
4384	-112.694984	6.884749	7.940299	7.266403	0.782477	ARDL(1, 3, 2, 4, 4, 3, 1)
5008	-112.703316	6.885166	7.940715	7.266819	0.782387	ARDL(1, 3, 1, 4, 4, 3, 2)
2523	-115.705612	6.885281	7.814164	7.221136	0.789284	ARDL(1, 4, 0, 4, 4, 0, 2)
141	-109.706975	6.885349	8.067564	7.312801	0.765830	ARDL(1, 4, 4, 3, 4, 1, 4)
1251	-107.770337	6.888517	8.155176	7.346501	0.744931	ARDL(1, 4, 2, 4, 4, 4, 4)
126	-106.804415	6.890221	8.199102	7.363471	0.729952	ARDL(1, 4, 4, 3, 4, 4, 4)
1502	-110.836468	6.891823	8.031817	7.304009	0.771285	ARDL(1, 4, 2, 2, 4, 4, 3)
1378	-110.843616	6.892181	8.032174	7.304366	0.771203	ARDL(1, 4, 2, 3, 4, 4, 2)
2764	-116.886604	6.894330	7.780992	7.214919	0.788231	ARDL(1, 4, 0, 2, 4, 2, 1)
2018	-114.915013	6.895751	7.866856	7.246872	0.785536	ARDL(1, 4, 1, 3, 4, 1, 2)
5639	-115.917868	6.895893	7.824777	7.231748	0.787035	ARDL(1, 3, 0, 4, 4, 2, 1)
2131	-111.919489	6.895974	7.993746	7.292894	0.775804	ARDL(1, 4, 1, 2, 4, 3, 4)
1256	-108.934030	6.896702	8.121139	7.339419	0.754226	ARDL(1, 4, 2, 4, 4, 3, 4)
1512	-112.948621	6.897431	7.952981	7.279084	0.779701	ARDL(1, 4, 2, 2, 4, 2, 3)
2756	-112.951324	6.897566	7.953116	7.279220	0.779671	ARDL(1, 4, 0, 2, 4, 3, 4)
2636	-112.961842	6.898092	7.953642	7.279746	0.779555	ARDL(1, 4, 0, 3, 4, 2, 4)
5644	-116.966204	6.898310	7.784972	7.218899	0.787387	ARDL(1, 3, 0, 4, 4, 1, 1)
252	-108.968665	6.898433	8.122871	7.341151	0.753800	ARDL(1, 4, 4, 2, 4, 4, 3)
2641	-113.979000	6.898950	7.912278	7.265337	0.782551	ARDL(1, 4, 0, 3, 4, 1, 4)
2143	-115.985426	6.899271	7.828155	7.235126	0.786315	ARDL(1, 4, 1, 2, 4, 1, 2)
2012	-112.988179	6.899409	7.954959	7.281062	0.779265	ARDL(1, 4, 1, 3, 4, 2, 3)
2634	-115.006942	6.900347	7.871453	7.251468	0.784548	ARDL(1, 4, 0, 3, 4, 3, 1)
753	-110.007008	6.900350	8.082566	7.327802	0.762291	ARDL(1, 4, 3, 3, 4, 4, 2)
1896	-113.038673	6.901934	7.957483	7.283587	0.778707	ARDL(1, 4, 1, 4, 4, 0, 4)
128	-109.043412	6.902171	8.126608	7.344889	0.752879	ARDL(1, 4, 4, 3, 4, 4, 2)
2648	-117.047106	6.902355	7.789017	7.222944	0.786525	ARDL(1, 4, 0, 3, 4, 0, 2)
2759	-116.094720	6.904736	7.833620	7.240591	0.785144	ARDL(1, 4, 0, 2, 4, 3, 1)
2016	-113.117715	6.905886	7.961435	7.287539	0.777831	ARDL(1, 4, 1, 3, 4, 1, 4)
2011	-112.124123	6.906206	8.003978	7.303126	0.773498	ARDL(1, 4, 1, 3, 4, 2, 4)
649	-114.124671	6.906234	7.919561	7.272621	0.780961	ARDL(1, 4, 3, 4, 4, 0, 1)
1511	-112.125749	6.906287	8.004059	7.303207	0.773480	ARDL(1, 4, 2, 2, 4, 2, 4)
2132	-113.128967	6.906448	7.961998	7.288102	0.777706	ARDL(1, 4, 1, 2, 4, 3, 3)
5884	-117.129806	6.906490	7.793152	7.227079	0.785640	ARDL(1, 3, 0, 2, 4, 3, 1)

Appendix J: Model Selection Plot for ARDL Specifications, Manufacturing Sector



Appendix K: Model selection Criteria Table for the Service Sector

Model Selection Criteria Table
Dependent Variable: SVA
Date: 03/17/26 Time: 15:02
Sample: 1981 2024
Included observations: 40

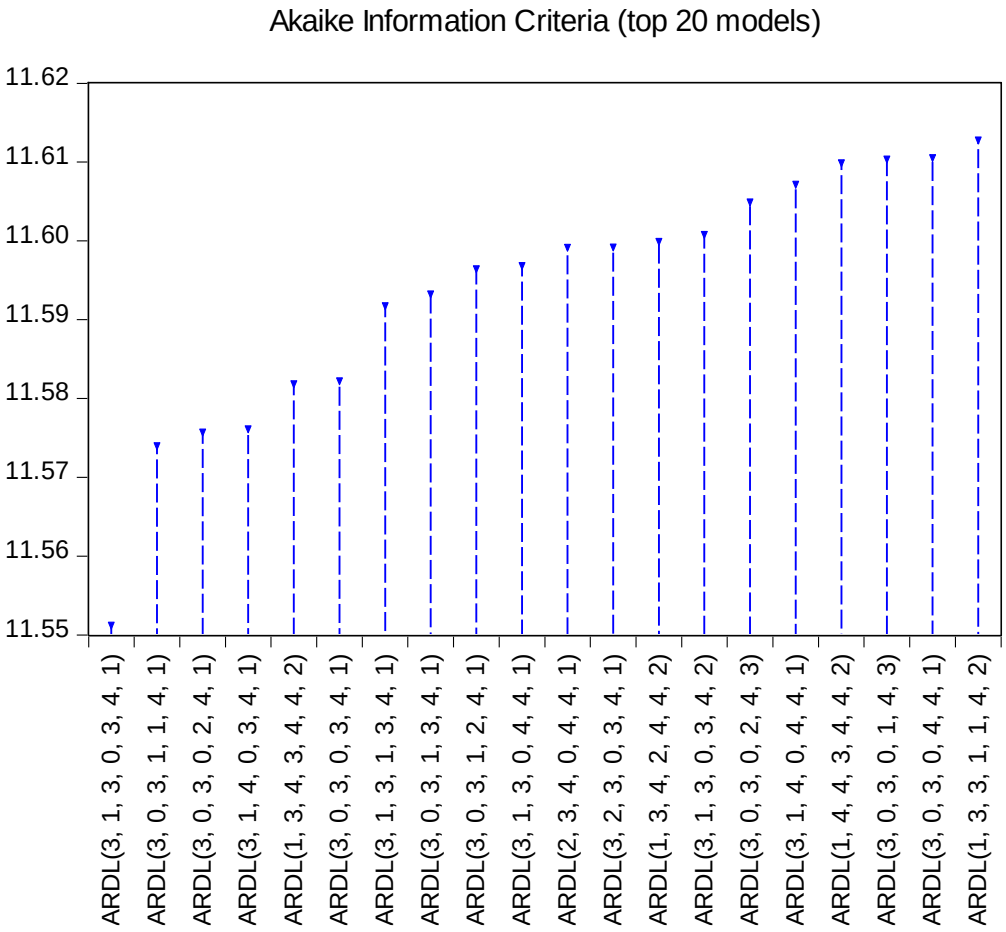
Model	LogL	AIC*	BIC	HQ	Adj. R-sq	Specification
10529	-209.024724	11.551236	12.480120	11.887091	0.777627	ARDL(3, 1, 3, 0, 3, 4, 1)
13579	-211.480208	11.574010	12.418450	11.879333	0.773721	ARDL(3, 0, 3, 1, 1, 4, 1)
13679	-211.515127	11.575756	12.420196	11.881079	0.773326	ARDL(3, 0, 3, 0, 2, 4, 1)
9904	-208.523135	11.576157	12.547262	11.927278	0.770378	ARDL(3, 1, 4, 0, 3, 4, 1)
34503	-203.637396	11.581870	12.764085	12.009322	0.745206	ARDL(1, 3, 4, 3, 4, 4, 2)
13654	-210.644876	11.582244	12.468906	11.902833	0.771555	ARDL(3, 0, 3, 0, 3, 4, 1)
10404	-208.835575	11.591779	12.562884	11.942900	0.766763	ARDL(3, 1, 3, 1, 3, 4, 1)
13529	-209.865473	11.593274	12.522157	11.929129	0.768080	ARDL(3, 0, 3, 1, 3, 4, 1)
13554	-210.929217	11.596461	12.483123	11.917050	0.768284	ARDL(3, 0, 3, 1, 2, 4, 1)
10504	-208.937380	11.596869	12.567975	11.947990	0.765572	ARDL(3, 1, 3, 0, 4, 4, 1)
19254	-206.983752	11.599188	12.654737	11.980841	0.759041	ARDL(2, 3, 4, 0, 4, 4, 1)
7404	-208.984549	11.599227	12.570333	11.950349	0.765019	ARDL(3, 2, 3, 0, 3, 4, 1)
34628	-204.998844	11.599942	12.739936	12.012128	0.748238	ARDL(1, 3, 4, 2, 4, 4, 2)
10528	-209.016442	11.600822	12.571928	11.951943	0.764644	ARDL(3, 1, 3, 0, 3, 4, 2)
13677	-210.099155	11.604958	12.533841	11.940813	0.765354	ARDL(3, 0, 3, 0, 2, 4, 3)
9879	-208.143673	11.607184	12.620511	11.973571	0.760612	ARDL(3, 1, 4, 0, 4, 4, 1)
31378	-203.198144	11.609907	12.834345	12.052625	0.728081	ARDL(1, 4, 4, 3, 4, 4, 2)
13702	-211.207659	11.610383	12.497045	11.930972	0.765035	ARDL(3, 0, 3, 0, 1, 4, 3)
13629	-210.211407	11.610570	12.539454	11.946425	0.764034	ARDL(3, 0, 3, 0, 4, 4, 1)
35453	-210.256340	11.612817	12.541701	11.948672	0.763503	ARDL(1, 3, 3, 1, 1, 4, 2)
19255	-208.276501	11.613825	12.627153	11.980212	0.759017	ARDL(2, 3, 4, 0, 4, 4, 0)
34703	-208.288343	11.614417	12.627745	11.980804	0.758874	ARDL(1, 3, 4, 2, 1, 4, 2)
13652	-209.305210	11.615260	12.586366	11.966382	0.761221	ARDL(3, 0, 3, 0, 3, 4, 3)
13054	-211.357811	11.617891	12.504552	11.938479	0.763265	ARDL(3, 0, 4, 0, 2, 4, 1)
13578	-211.385032	11.619252	12.505913	11.939841	0.762942	ARDL(3, 0, 3, 1, 1, 4, 2)
10554	-211.404906	11.620245	12.506907	11.940834	0.762707	ARDL(3, 1, 3, 0, 2, 4, 1)
9779	-208.405558	11.620278	12.633606	11.986665	0.757457	ARDL(3, 1, 4, 1, 3, 4, 1)
10454	-211.423909	11.621195	12.507857	11.941784	0.762481	ARDL(3, 1, 3, 1, 1, 4, 1)
29204	-213.428054	11.621403	12.423620	11.911459	0.762452	ARDL(2, 0, 3, 1, 1, 4, 1)
13676	-209.435715	11.621786	12.592891	11.972907	0.759658	ARDL(3, 0, 3, 0, 2, 4, 4)
13029	-210.443478	11.622174	12.551058	11.958029	0.761280	ARDL(3, 0, 4, 0, 3, 4, 1)
13454	-211.454189	11.622709	12.509371	11.943298	0.762121	ARDL(3, 0, 3, 2, 1, 4, 1)
12954	-211.464254	11.623213	12.509874	11.943802	0.762001	ARDL(3, 0, 4, 1, 1, 4, 1)
9903	-208.482149	11.624107	12.637435	11.990495	0.756526	ARDL(3, 1, 4, 0, 3, 4, 2)
19829	-210.489881	11.624494	12.553378	11.960349	0.760725	ARDL(2, 3, 3, 1, 1, 4, 1)
13678	-211.515102	11.625755	12.512417	11.946344	0.761396	ARDL(3, 0, 3, 0, 2, 4, 2)
6779	-208.515395	11.625770	12.639097	11.992157	0.756121	ARDL(3, 2, 4, 0, 3, 4, 1)
35454	-211.526000	11.626300	12.512962	11.946889	0.761266	ARDL(1, 3, 3, 1, 1, 4, 1)
3629	-206.533063	11.626653	12.724425	12.023573	0.747582	ARDL(3, 3, 4, 0, 4, 4, 1)
4204	-209.536367	11.626818	12.597924	11.977939	0.758445	ARDL(3, 3, 3, 1, 1, 4, 1)
13404	-209.558820	11.627941	12.599047	11.979062	0.758174	ARDL(3, 0, 3, 2, 3, 4, 1)
13004	-209.576384	11.628819	12.599925	11.979940	0.757962	ARDL(3, 0, 4, 0, 4, 4, 1)
34627	-204.592072	11.629604	12.811819	12.057055	0.732749	ARDL(1, 3, 4, 2, 4, 4, 3)
34502	-203.613850	11.630693	12.855130	12.073410	0.722370	ARDL(1, 3, 4, 3, 4, 4, 3)
18878	-203.632902	11.631645	12.856083	12.074363	0.722106	ARDL(2, 3, 4, 3, 4, 4, 2)
34378	-203.637044	11.631852	12.856290	12.074570	0.722048	ARDL(1, 3, 4, 4, 4, 4, 2)
19253	-206.640751	11.632038	12.729809	12.028957	0.746219	ARDL(2, 3, 4, 0, 4, 4, 2)

13653	-210.643638	11.632182	12.561066	11.968037	0.758879	ARDL(3, 0, 3, 0, 3, 4, 2)
10527	-208.672113	11.633606	12.646933	11.999993	0.754203	ARDL(3, 1, 3, 0, 3, 4, 3)
10279	-208.695921	11.634796	12.648124	12.001183	0.753910	ARDL(3, 1, 3, 2, 3, 4, 1)
16129	-206.695977	11.634799	12.732570	12.031718	0.745517	ARDL(2, 4, 4, 0, 4, 4, 1)
35328	-209.698220	11.634911	12.606017	11.986032	0.756483	ARDL(1, 3, 3, 2, 1, 4, 2)
12904	-209.700921	11.635046	12.606152	11.986167	0.756450	ARDL(3, 0, 4, 1, 3, 4, 1)
34578	-207.756657	11.637833	12.693382	12.019486	0.749546	ARDL(1, 3, 4, 3, 1, 4, 2)
13577	-210.757393	11.637870	12.566753	11.973725	0.757503	ARDL(3, 0, 3, 1, 1, 4, 3)
13504	-209.778385	11.638919	12.610025	11.990040	0.755505	ARDL(3, 0, 3, 1, 4, 4, 1)
4279	-208.782933	11.639147	12.652474	12.005534	0.752837	ARDL(3, 3, 3, 0, 3, 4, 1)
7279	-208.797915	11.639896	12.653223	12.006283	0.752652	ARDL(3, 2, 3, 1, 3, 4, 1)
12929	-210.803547	11.640177	12.569061	11.976032	0.756943	ARDL(3, 0, 4, 1, 2, 4, 1)
31503	-204.810847	11.640542	12.822758	12.067994	0.729810	ARDL(1, 4, 4, 2, 4, 4, 2)
10379	-208.815600	11.640780	12.654108	12.007167	0.752433	ARDL(3, 1, 3, 1, 4, 4, 1)
13701	-210.823087	11.641154	12.570038	11.977009	0.756705	ARDL(3, 0, 3, 0, 1, 4, 4)
13704	-213.824130	11.641207	12.443424	11.931263	0.757700	ARDL(3, 0, 3, 0, 1, 4, 1)
7379	-208.824158	11.641208	12.654536	12.007595	0.752327	ARDL(3, 2, 3, 0, 4, 4, 1)
10403	-208.830770	11.641539	12.654866	12.007926	0.752245	ARDL(3, 1, 3, 1, 3, 4, 2)
34828	-209.832356	11.641618	12.612724	11.992739	0.754844	ARDL(1, 3, 4, 1, 1, 4, 2)
13052	-209.850913	11.642546	12.613651	11.993667	0.754616	ARDL(3, 0, 4, 0, 2, 4, 3)
13528	-209.863621	11.643181	12.614287	11.994302	0.754460	ARDL(3, 0, 3, 1, 3, 4, 2)
44829	-214.863905	11.643195	12.403191	11.917986	0.756372	ARDL(1, 0, 3, 1, 1, 4, 1)
19130	-207.882896	11.644145	12.699694	12.025798	0.747961	ARDL(2, 3, 4, 1, 4, 4, 0)
18879	-204.904329	11.645216	12.827432	12.072668	0.728544	ARDL(2, 3, 4, 3, 4, 4, 1)
19129	-206.910948	11.645547	12.743319	12.042467	0.742767	ARDL(2, 3, 4, 1, 4, 4, 1)
34702	-207.923754	11.646188	12.701737	12.027841	0.747445	ARDL(1, 3, 4, 2, 1, 4, 3)
13429	-210.924481	11.646224	12.575108	11.982079	0.755469	ARDL(3, 0, 3, 2, 2, 4, 1)
10429	-210.925503	11.646275	12.575159	11.982130	0.755456	ARDL(3, 1, 3, 1, 2, 4, 1)
13553	-210.929212	11.646461	12.575344	11.982316	0.755411	ARDL(3, 0, 3, 1, 2, 4, 2)
10503	-208.936105	11.646805	12.660133	12.013193	0.750937	ARDL(3, 1, 3, 0, 4, 4, 2)
13651	-208.939433	11.646972	12.660299	12.013359	0.750895	ARDL(3, 0, 3, 0, 3, 4, 4)
34701	-206.949853	11.647493	12.745264	12.044412	0.742266	ARDL(1, 3, 4, 2, 1, 4, 4)
19003	-204.972037	11.648602	12.830817	12.076054	0.727623	ARDL(2, 3, 4, 2, 4, 4, 2)
7403	-208.979386	11.648969	12.662297	12.015357	0.750397	ARDL(3, 2, 3, 0, 3, 4, 2)
19252	-205.997576	11.649879	12.789872	12.062064	0.735347	ARDL(2, 3, 4, 0, 4, 4, 3)
26079	-213.003875	11.650194	12.494634	11.955517	0.755809	ARDL(2, 1, 3, 1, 1, 4, 1)
13027	-209.012260	11.650613	12.663941	12.017000	0.749986	ARDL(3, 0, 4, 0, 3, 4, 3)
10577	-211.019102	11.650955	12.579839	11.986810	0.754309	ARDL(3, 1, 3, 0, 1, 4, 3)
6754	-208.040877	11.652044	12.707594	12.033697	0.745962	ARDL(3, 2, 4, 0, 4, 4, 1)
16130	-208.047789	11.652389	12.707939	12.034043	0.745874	ARDL(2, 4, 4, 0, 4, 4, 0)
13727	-213.063157	11.653158	12.497598	11.958481	0.755084	ARDL(3, 0, 3, 0, 0, 4, 3)
19204	-210.066344	11.653317	12.624423	12.004438	0.751959	ARDL(2, 3, 4, 1, 1, 4, 1)
9654	-208.080638	11.654032	12.709582	12.035685	0.745456	ARDL(3, 1, 4, 2, 3, 4, 1)
13552	-210.085626	11.654281	12.625387	12.005402	0.751720	ARDL(3, 0, 3, 1, 2, 4, 3)
4327	-209.087804	11.654390	12.667718	12.020778	0.749040	ARDL(3, 3, 3, 0, 1, 4, 3)
10552	-210.089304	11.654465	12.625571	12.005586	0.751674	ARDL(3, 1, 3, 0, 2, 4, 3)
35429	-211.091716	11.654586	12.583470	11.990441	0.753415	ARDL(1, 3, 3, 1, 2, 4, 1)
31377	-203.097628	11.654881	12.921541	12.112866	0.702389	ARDL(1, 4, 4, 3, 4, 4, 3)
29179	-213.111411	11.655571	12.500010	11.960893	0.754492	ARDL(2, 0, 3, 1, 2, 4, 1)
9878	-208.130255	11.656513	12.712062	12.038166	0.744824	ARDL(3, 1, 4, 0, 4, 4, 2)
9754	-208.140080	11.657004	12.712554	12.038657	0.744699	ARDL(3, 1, 4, 1, 4, 4, 1)
504	-206.150359	11.657518	12.797512	12.069704	0.733317	ARDL(3, 4, 4, 0, 4, 4, 1)
31578	-208.154963	11.657748	12.713298	12.039402	0.744509	ARDL(1, 4, 4, 2, 1, 4, 2)
9902	-208.165086	11.658254	12.713804	12.039908	0.744379	ARDL(3, 1, 4, 0, 3, 4, 3)
13329	-211.175827	11.658791	12.587675	11.994646	0.752376	ARDL(3, 0, 3, 3, 1, 4, 1)
31502	-204.177684	11.658884	12.883322	12.101602	0.714432	ARDL(1, 4, 4, 2, 4, 4, 3)
10526	-208.178939	11.658947	12.714497	12.040600	0.744202	ARDL(3, 1, 3, 0, 3, 4, 4)

13627	-209.180811	11.659041	12.672368	12.025428	0.747871	ARDL(3, 0, 3, 0, 4, 4, 3)
3654	-208.181281	11.659064	12.714614	12.040717	0.744172	ARDL(3, 3, 4, 0, 3, 4, 1)
13051	-209.181541	11.659077	12.672405	12.025464	0.747861	ARDL(3, 0, 4, 0, 2, 4, 4)
13077	-211.189220	11.659461	12.588345	11.995316	0.752210	ARDL(3, 0, 4, 0, 1, 4, 3)
31253	-203.192606	11.659630	12.926290	12.117614	0.700972	ARDL(1, 4, 4, 4, 4, 4, 2)
13628	-210.192911	11.659646	12.630751	12.010767	0.750384	ARDL(3, 0, 3, 0, 4, 4, 2)
19828	-210.196215	11.659811	12.630916	12.010932	0.750343	ARDL(2, 3, 3, 1, 1, 4, 2)
15753	-203.197790	11.659890	12.926549	12.117874	0.700895	ARDL(2, 4, 4, 3, 4, 4, 2)
3630	-208.201099	11.660055	12.715605	12.041708	0.743919	ARDL(3, 3, 4, 0, 4, 4, 0)
12779	-209.201420	11.660071	12.673399	12.026458	0.747611	ARDL(3, 0, 4, 2, 3, 4, 1)
3579	-209.207779	11.660389	12.673717	12.026776	0.747530	ARDL(3, 3, 4, 1, 1, 4, 1)
9929	-211.215917	11.660796	12.589680	11.996651	0.751879	ARDL(3, 1, 4, 0, 2, 4, 1)
10534	-212.219075	11.660954	12.547615	11.981543	0.752847	ARDL(3, 1, 3, 0, 3, 3, 1)
13279	-209.226548	11.661327	12.674655	12.027715	0.747293	ARDL(3, 0, 3, 3, 3, 4, 1)
34678	-208.231476	11.661574	12.717123	12.043227	0.743529	ARDL(1, 3, 4, 2, 2, 4, 2)
13527	-209.231693	11.661585	12.674912	12.027972	0.747228	ARDL(3, 0, 3, 1, 3, 4, 3)
3403	-205.236380	11.661819	12.844035	12.089271	0.723999	ARDL(3, 3, 4, 2, 3, 4, 2)
19078	-208.237994	11.661900	12.717449	12.043553	0.743446	ARDL(2, 3, 4, 2, 1, 4, 2)
3627	-205.247331	11.662367	12.844582	12.089818	0.723848	ARDL(3, 3, 4, 0, 4, 4, 3)
32328	-210.248208	11.662410	12.633516	12.013532	0.749693	ARDL(1, 4, 3, 1, 1, 4, 2)
35452	-210.248237	11.662412	12.633518	12.013533	0.749693	ARDL(1, 3, 3, 1, 1, 4, 3)
13703	-213.253608	11.662680	12.507120	11.968003	0.752740	ARDL(3, 0, 3, 0, 1, 4, 2)
35428	-210.254422	11.662721	12.633827	12.013842	0.749615	ARDL(1, 3, 3, 1, 2, 4, 2)
7429	-211.258794	11.662940	12.591823	11.998795	0.751347	ARDL(3, 2, 3, 0, 2, 4, 1)
3628	-206.269469	11.663473	12.803467	12.075659	0.731724	ARDL(3, 3, 4, 0, 4, 4, 2)
4254	-208.283970	11.664199	12.719748	12.045852	0.742855	ARDL(3, 3, 3, 0, 4, 4, 1)
16128	-206.285403	11.664270	12.804264	12.076456	0.731511	ARDL(2, 4, 4, 0, 4, 4, 2)
44828	-214.290159	11.664508	12.466726	11.954565	0.751988	ARDL(1, 0, 3, 1, 1, 4, 2)
3452	-206.307400	11.665370	12.805364	12.077556	0.731215	ARDL(3, 3, 4, 2, 1, 4, 3)
28629	-211.311841	11.665592	12.594476	12.001447	0.750687	ARDL(2, 0, 4, 0, 4, 4, 1)
34504	-206.312245	11.665612	12.805606	12.077798	0.731150	ARDL(1, 3, 4, 3, 4, 4, 1)
1129	-207.321701	11.666085	12.763857	12.063005	0.737430	ARDL(3, 4, 3, 0, 4, 4, 1)
7329	-211.331269	11.666563	12.595447	12.002418	0.750444	ARDL(3, 2, 3, 1, 1, 4, 1)
4202	-208.331590	11.666579	12.722129	12.048233	0.742242	ARDL(3, 3, 3, 1, 1, 4, 3)
13576	-210.338428	11.666921	12.638027	12.018043	0.748561	ARDL(3, 0, 3, 1, 1, 4, 4)
10453	-211.338609	11.666930	12.595814	12.002785	0.750353	ARDL(3, 1, 3, 1, 1, 4, 2)
4154	-208.342898	11.667145	12.722695	12.048798	0.742096	ARDL(3, 3, 3, 1, 3, 4, 1)
13053	-211.354407	11.667720	12.596604	12.003575	0.750155	ARDL(3, 0, 4, 0, 2, 4, 2)
1154	-208.356232	11.667812	12.723361	12.049465	0.741924	ARDL(3, 4, 3, 0, 3, 4, 1)
4302	-208.358718	11.667936	12.723486	12.049589	0.741892	ARDL(3, 3, 3, 0, 2, 4, 3)
10329	-211.366356	11.668318	12.597202	12.004173	0.750006	ARDL(3, 1, 3, 2, 1, 4, 1)
12953	-211.368772	11.668439	12.597322	12.004294	0.749976	ARDL(3, 0, 4, 1, 1, 4, 2)
3677	-207.373504	11.668675	12.766447	12.065595	0.736749	ARDL(3, 3, 4, 0, 2, 4, 3)
9778	-208.373822	11.668691	12.724241	12.050345	0.741697	ARDL(3, 1, 4, 1, 3, 4, 2)
12879	-209.377600	11.668880	12.682208	12.035267	0.745377	ARDL(3, 0, 4, 1, 4, 4, 1)
13453	-211.384384	11.669219	12.598103	12.005074	0.749781	ARDL(3, 0, 3, 2, 1, 4, 2)
28579	-213.388319	11.669416	12.513856	11.974739	0.751069	ARDL(2, 0, 4, 1, 1, 4, 1)
29203	-213.388773	11.669439	12.513878	11.974761	0.751064	ARDL(2, 0, 3, 1, 1, 4, 2)
29079	-213.392572	11.669629	12.514068	11.974951	0.751016	ARDL(2, 0, 3, 2, 1, 4, 1)
502	-204.396276	11.669814	12.894251	12.112532	0.711294	ARDL(3, 4, 4, 0, 4, 4, 3)
34501	-203.397194	11.669860	12.936519	12.127844	0.697898	ARDL(1, 3, 4, 3, 4, 4, 4)
6654	-208.397390	11.669869	12.725419	12.051523	0.741393	ARDL(3, 2, 4, 1, 3, 4, 1)
15754	-204.401795	11.670090	12.894527	12.112808	0.711214	ARDL(2, 4, 4, 3, 4, 4, 1)
10553	-211.403372	11.670169	12.599052	12.006024	0.749543	ARDL(3, 1, 3, 0, 2, 4, 2)
4203	-209.407761	11.670388	12.683716	12.036775	0.744993	ARDL(3, 3, 3, 1, 1, 4, 2)
9829	-211.408353	11.670418	12.599301	12.006273	0.749481	ARDL(3, 1, 4, 1, 1, 4, 1)
34878	-208.413244	11.670662	12.726212	12.052316	0.741188	ARDL(1, 3, 4, 0, 4, 4, 2)

34576	-206.413726	11.670686	12.810680	12.082872	0.729782	ARDL(1, 3, 4, 3, 1, 4, 4)
16127	-205.416183	11.670809	12.853025	12.098261	0.721507	ARDL(2, 4, 4, 0, 4, 4, 3)
12829	-211.421033	11.671052	12.599935	12.006907	0.749322	ARDL(3, 0, 4, 2, 1, 4, 1)
10551	-209.421134	11.671057	12.684384	12.037444	0.744823	ARDL(3, 1, 3, 0, 2, 4, 4)
13403	-209.427756	11.671388	12.684715	12.037775	0.744738	ARDL(3, 0, 3, 2, 3, 4, 2)
13551	-209.431768	11.671588	12.684916	12.037976	0.744687	ARDL(3, 0, 3, 1, 2, 4, 4)
13028	-210.442909	11.672145	12.643251	12.023267	0.747244	ARDL(3, 0, 4, 0, 3, 4, 2)
19704	-210.444513	11.672226	12.643331	12.023347	0.747224	ARDL(2, 3, 3, 2, 1, 4, 1)
34626	-204.446134	11.672307	12.896744	12.115025	0.710573	ARDL(1, 3, 4, 2, 4, 4, 4)
29254	-212.460996	11.673050	12.559712	11.993639	0.749840	ARDL(2, 0, 3, 0, 4, 4, 1)
3676	-206.474396	11.673720	12.813713	12.085905	0.728961	ARDL(3, 3, 4, 0, 2, 4, 4)
19804	-210.476470	11.673824	12.644929	12.024945	0.746820	ARDL(2, 3, 3, 1, 2, 4, 1)
29304	-214.477852	11.673893	12.476110	11.963949	0.749650	ARDL(2, 0, 3, 0, 2, 4, 1)
6778	-208.478160	11.673908	12.729458	12.055561	0.740346	ARDL(3, 2, 4, 0, 3, 4, 2)
4179	-209.480163	11.674008	12.687336	12.040395	0.744068	ARDL(3, 3, 3, 1, 2, 4, 1)
35329	-211.487961	11.674398	12.603282	12.010253	0.748481	ARDL(1, 3, 3, 2, 1, 4, 1)
16704	-210.489857	11.674493	12.645599	12.025614	0.746650	ARDL(2, 4, 3, 1, 1, 4, 1)
16005	-207.499476	11.674974	12.772745	12.071893	0.735085	ARDL(2, 4, 4, 1, 4, 4, 0)
4304	-210.501993	11.675100	12.646205	12.026221	0.746497	ARDL(3, 3, 3, 0, 2, 4, 1)
9653	-207.510234	11.675512	12.773283	12.072431	0.734943	ARDL(3, 1, 4, 2, 3, 4, 2)
3504	-206.510715	11.675536	12.815529	12.087721	0.728469	ARDL(3, 3, 4, 1, 4, 4, 1)
34829	-211.514633	11.675732	12.604615	12.011587	0.748146	ARDL(1, 3, 4, 1, 1, 4, 1)
32329	-211.525410	11.676270	12.605154	12.012125	0.748010	ARDL(1, 4, 3, 1, 1, 4, 1)
4079	-209.525979	11.676299	12.689627	12.042686	0.743481	ARDL(3, 3, 3, 2, 1, 4, 1)
1079	-209.528185	11.676409	12.689737	12.042797	0.743453	ARDL(3, 4, 3, 1, 1, 4, 1)
19128	-206.549111	11.677456	12.817449	12.089641	0.727947	ARDL(2, 3, 4, 1, 4, 4, 2)
13379	-209.549562	11.677478	12.690806	12.043865	0.743179	ARDL(3, 0, 3, 2, 4, 4, 1)
34653	-207.553143	11.677657	12.775429	12.074577	0.734374	ARDL(1, 3, 4, 2, 3, 4, 2)
10278	-208.564842	11.678242	12.733792	12.059896	0.739219	ARDL(3, 1, 3, 2, 3, 4, 2)
7154	-208.567733	11.678387	12.733936	12.060040	0.739181	ARDL(3, 2, 3, 2, 3, 4, 1)
41704	-214.570517	11.678526	12.480744	11.968582	0.748487	ARDL(1, 1, 3, 1, 1, 4, 1)
13003	-209.570643	11.678532	12.691860	12.044919	0.742908	ARDL(3, 0, 4, 0, 4, 4, 2)
12654	-208.574311	11.678716	12.734265	12.060369	0.739095	ARDL(3, 0, 4, 3, 3, 4, 1)
10452	-210.575547	11.678777	12.649883	12.029898	0.745563	ARDL(3, 1, 3, 1, 1, 4, 3)
34453	-207.583553	11.679178	12.776949	12.076097	0.733969	ARDL(1, 3, 4, 4, 1, 4, 2)
3378	-204.584343	11.679217	12.903655	12.121935	0.708566	ARDL(3, 3, 4, 2, 4, 4, 2)
19002	-204.591359	11.679568	12.904006	12.122286	0.708464	ARDL(2, 3, 4, 2, 4, 4, 3)
35203	-209.611522	11.680576	12.693904	12.046963	0.742382	ARDL(1, 3, 3, 3, 1, 4, 2)
18877	-203.612476	11.680624	12.947283	12.138608	0.694628	ARDL(2, 3, 4, 3, 4, 4, 3)

Appendix L: Model Selection Plot for ARDL Specifications, Service Sector



Appendix M: Model selection Criteria Table for the Agriculture Sector

Model Selection Criteria Table
Dependent Variable: AVA
Date: 03/17/26 Time: 16:51
Sample: 1981 2024
Included observations: 41

Model	LogL	AIC*	BIC	HQ	Adj. R-sq	Specification
2151	-187.104311	10.005088	10.757388	10.279034	0.508290	ARDL(1, 1, 3, 2, 1, 2, 1)
2214	-187.107367	10.005237	10.757537	10.279184	0.508217	ARDL(1, 1, 3, 1, 1, 2, 2)
2088	-187.243085	10.011858	10.764158	10.285804	0.504950	ARDL(1, 1, 3, 3, 1, 2, 0)
2213	-186.324341	10.015821	10.809916	10.304987	0.505131	ARDL(1, 1, 3, 1, 1, 2, 3)
2150	-186.401761	10.019598	10.813692	10.308763	0.503258	ARDL(1, 1, 3, 2, 1, 2, 2)
2149	-185.611417	10.029825	10.865714	10.334210	0.499285	ARDL(1, 1, 3, 2, 1, 2, 3)
2087	-186.650434	10.031729	10.825823	10.320894	0.497196	ARDL(1, 1, 3, 3, 1, 2, 1)
2230	-188.775726	10.037840	10.748346	10.296567	0.488748	ARDL(1, 1, 3, 1, 0, 2, 2)
552	-187.824028	10.040197	10.792496	10.314143	0.490720	ARDL(1, 3, 1, 3, 1, 2, 0)
2134	-185.830530	10.040514	10.876402	10.344898	0.493905	ARDL(1, 1, 3, 2, 2, 2, 2)
2215	-188.837140	10.040836	10.751342	10.299563	0.487214	ARDL(1, 1, 3, 1, 1, 2, 1)
2152	-188.841134	10.041031	10.751536	10.299758	0.487115	ARDL(1, 1, 3, 2, 1, 2, 0)
2198	-186.875095	10.042688	10.836782	10.331853	0.491655	ARDL(1, 1, 3, 1, 2, 2, 2)
2210	-186.898625	10.043835	10.837930	10.333001	0.491072	ARDL(1, 1, 3, 1, 1, 3, 2)
40	-185.913393	10.044556	10.880445	10.348940	0.491855	ARDL(1, 3, 3, 3, 1, 2, 0)
1127	-186.942095	10.045956	10.840050	10.335121	0.489991	ARDL(1, 2, 3, 2, 1, 2, 1)
2135	-186.946751	10.046183	10.840277	10.335348	0.489875	ARDL(1, 1, 3, 2, 2, 2, 1)
2209	-185.960512	10.046854	10.882743	10.351239	0.490685	ARDL(1, 1, 3, 1, 1, 3, 3)
808	-188.963770	10.047013	10.757519	10.305740	0.484037	ARDL(1, 3, 0, 3, 1, 2, 0)
816	-190.965296	10.047088	10.674004	10.275376	0.474880	ARDL(1, 3, 0, 3, 1, 0, 0)
2229	-188.009464	10.049242	10.801542	10.323188	0.486093	ARDL(1, 1, 3, 1, 0, 2, 3)
1190	-187.045079	10.050979	10.845074	10.340145	0.487423	ARDL(1, 2, 3, 1, 1, 2, 2)
2072	-187.073273	10.052355	10.846449	10.341520	0.486717	ARDL(1, 1, 3, 3, 2, 2, 0)
2147	-187.089096	10.053127	10.847221	10.342292	0.486321	ARDL(1, 1, 3, 2, 1, 3, 1)
2133	-185.146784	10.055941	10.933624	10.375545	0.486032	ARDL(1, 1, 3, 2, 2, 2, 3)
2197	-186.157220	10.056450	10.892339	10.360834	0.485775	ARDL(1, 1, 3, 1, 2, 2, 3)
296	-187.203827	10.058723	10.852818	10.347889	0.483438	ARDL(1, 3, 2, 3, 1, 2, 0)
2084	-187.216947	10.059363	10.853458	10.348529	0.483107	ARDL(1, 1, 3, 3, 1, 3, 0)
1064	-187.217351	10.059383	10.853477	10.348548	0.483097	ARDL(1, 2, 3, 3, 1, 2, 0)
103	-186.269891	10.061946	10.897835	10.366331	0.482941	ARDL(1, 3, 3, 2, 1, 2, 1)
2146	-186.285232	10.062694	10.898583	10.367079	0.482554	ARDL(1, 1, 3, 2, 1, 3, 2)
2086	-186.288586	10.062858	10.898747	10.367242	0.482469	ARDL(1, 1, 3, 3, 1, 2, 2)
1189	-186.312616	10.064030	10.899919	10.368415	0.481862	ARDL(1, 2, 3, 1, 1, 2, 3)
1126	-186.349331	10.065821	10.901710	10.370206	0.480933	ARDL(1, 2, 3, 2, 1, 2, 2)
2600	-190.351606	10.065932	10.734643	10.309440	0.469981	ARDL(1, 1, 1, 3, 1, 2, 0)
2145	-185.373367	10.066994	10.944677	10.386597	0.480319	ARDL(1, 1, 3, 2, 1, 3, 3)
2096	-190.383499	10.067488	10.736199	10.310995	0.469156	ARDL(1, 1, 3, 3, 1, 0, 0)
2294	-190.387995	10.067707	10.736418	10.311215	0.469040	ARDL(1, 1, 3, 0, 0, 2, 2)
812	-190.398967	10.068242	10.736953	10.311750	0.468755	ARDL(1, 3, 0, 3, 1, 1, 0)
804	-188.438360	10.070164	10.822464	10.344110	0.475228	ARDL(1, 3, 0, 3, 1, 3, 0)
2344	-189.447502	10.070610	10.781115	10.329337	0.471717	ARDL(1, 1, 2, 3, 1, 2, 0)
548	-187.454729	10.070962	10.865057	10.360128	0.477077	ARDL(1, 3, 1, 3, 1, 3, 0)
166	-186.472636	10.071836	10.907725	10.376221	0.477802	ARDL(1, 3, 3, 1, 1, 2, 2)
2071	-186.480760	10.072232	10.908121	10.376617	0.477595	ARDL(1, 1, 3, 3, 2, 2, 1)
2664	-191.485132	10.072445	10.699362	10.300734	0.461393	ARDL(1, 1, 1, 2, 1, 2, 0)
1191	-188.518560	10.074076	10.826376	10.348022	0.473171	ARDL(1, 2, 3, 1, 1, 2, 1)
2166	-188.524543	10.074368	10.826668	10.348314	0.473017	ARDL(1, 1, 3, 2, 0, 2, 2)

560	-190.534292	10.074843	10.743555	10.318351	0.465237	ARDL(1, 3, 1, 3, 1, 0, 0)
2194	-186.559791	10.076087	10.911976	10.380472	0.475577	ARDL(1, 1, 3, 1, 2, 3, 2)
1125	-185.603911	10.078240	10.955923	10.397843	0.474442	ARDL(1, 2, 3, 2, 1, 2, 3)
2130	-185.609122	10.078494	10.956177	10.398098	0.474308	ARDL(1, 1, 3, 2, 2, 3, 2)
2085	-185.611255	10.078598	10.956281	10.398202	0.474254	ARDL(1, 1, 3, 3, 1, 2, 3)
2083	-186.611474	10.078609	10.914497	10.382993	0.474253	ARDL(1, 1, 3, 3, 1, 3, 1)
2408	-190.614591	10.078761	10.747472	10.322268	0.463138	ARDL(1, 1, 2, 2, 1, 2, 0)
2278	-189.632220	10.079620	10.790126	10.338347	0.466936	ARDL(1, 1, 3, 0, 1, 2, 2)
2864	-193.635458	10.079778	10.623106	10.277628	0.444554	ARDL(1, 1, 0, 3, 1, 0, 0)
815	-190.636416	10.079825	10.748536	10.323333	0.462566	ARDL(1, 3, 0, 3, 1, 0, 1)
1063	-186.638270	10.079916	10.915804	10.384300	0.473565	ARDL(1, 2, 3, 3, 1, 2, 1)
39	-185.664392	10.081190	10.958873	10.400794	0.472889	ARDL(1, 3, 3, 3, 1, 2, 1)
2608	-192.678731	10.081889	10.667011	10.294959	0.450247	ARDL(1, 1, 1, 3, 1, 0, 0)
1186	-186.679407	10.081922	10.917811	10.386307	0.472508	ARDL(1, 2, 3, 1, 1, 3, 2)
2193	-185.680376	10.081970	10.959653	10.401573	0.472478	ARDL(1, 1, 3, 1, 2, 3, 3)
2216	-190.691511	10.082513	10.751224	10.326020	0.461120	ARDL(1, 1, 3, 1, 1, 2, 0)
2136	-188.696896	10.082775	10.835075	10.356722	0.468568	ARDL(1, 1, 3, 2, 2, 2, 0)
24	-185.705034	10.083172	10.960856	10.402776	0.471843	ARDL(1, 3, 3, 3, 2, 2, 0)
36	-185.712069	10.083516	10.961199	10.403119	0.471662	ARDL(1, 3, 3, 3, 1, 3, 0)
167	-187.722476	10.084023	10.878118	10.373189	0.470202	ARDL(1, 3, 3, 1, 1, 2, 1)
2226	-188.738467	10.084803	10.837103	10.358749	0.467489	ARDL(1, 1, 3, 1, 0, 3, 2)
2165	-187.756288	10.085673	10.879767	10.374838	0.469328	ARDL(1, 1, 3, 2, 0, 2, 3)
2117	-184.758910	10.085801	11.005278	10.420624	0.469121	ARDL(1, 1, 3, 2, 3, 2, 3)
832	-192.762843	10.085992	10.671115	10.299062	0.447987	ARDL(1, 3, 0, 3, 0, 0, 0)
2118	-185.764611	10.086079	10.963762	10.405682	0.470306	ARDL(1, 1, 3, 2, 3, 2, 2)
1128	-188.771626	10.086421	10.838721	10.360367	0.466627	ARDL(1, 2, 3, 2, 1, 2, 0)
824	-190.772562	10.086466	10.755178	10.329974	0.458985	ARDL(1, 3, 0, 3, 0, 2, 0)
616	-189.774524	10.086562	10.797068	10.345289	0.463222	ARDL(1, 3, 1, 2, 1, 2, 0)
1206	-188.775665	10.086618	10.838918	10.360564	0.466522	ARDL(1, 2, 3, 1, 0, 2, 2)
2070	-185.785448	10.087095	10.964778	10.406699	0.469767	ARDL(1, 1, 3, 3, 2, 2, 2)
2129	-184.788969	10.087267	11.006744	10.422090	0.468342	ARDL(1, 1, 3, 2, 2, 3, 3)
2352	-191.789442	10.087290	10.714206	10.315578	0.453339	ARDL(1, 1, 2, 3, 1, 0, 0)
102	-185.792426	10.087435	10.965119	10.407039	0.469587	ARDL(1, 3, 3, 2, 1, 2, 2)
2199	-188.793062	10.087466	10.839766	10.361413	0.466069	ARDL(1, 1, 3, 1, 2, 2, 1)
2663	-190.800113	10.087810	10.756521	10.331318	0.458258	ARDL(1, 1, 1, 2, 1, 2, 1)
2104	-189.802855	10.087944	10.798450	10.346671	0.462480	ARDL(1, 1, 3, 3, 0, 2, 0)
2211	-188.807110	10.088152	10.840452	10.362098	0.465703	ARDL(1, 1, 3, 1, 1, 3, 1)
162	-185.809040	10.088246	10.965929	10.407850	0.469157	ARDL(1, 3, 3, 1, 1, 3, 2)
551	-187.820777	10.088818	10.882913	10.377984	0.467656	ARDL(1, 3, 1, 3, 1, 2, 1)
104	-187.822310	10.088893	10.882988	10.378059	0.467616	ARDL(1, 3, 3, 2, 1, 2, 0)
536	-187.823706	10.088961	10.883056	10.378127	0.467580	ARDL(1, 3, 1, 3, 2, 2, 0)
1110	-185.825339	10.089041	10.966724	10.408645	0.468734	ARDL(1, 2, 3, 2, 2, 2, 2)
1185	-185.827678	10.089155	10.966838	10.408759	0.468674	ARDL(1, 2, 3, 1, 1, 3, 3)
1123	-186.832522	10.089391	10.925280	10.393776	0.468553	ARDL(1, 2, 3, 2, 1, 3, 1)
2604	-191.838508	10.089683	10.716600	10.317972	0.452029	ARDL(1, 1, 1, 3, 1, 1, 0)
2148	-188.839914	10.089752	10.842052	10.363698	0.464847	ARDL(1, 1, 3, 2, 1, 3, 0)
1111	-186.853924	10.090435	10.926324	10.394820	0.467998	ARDL(1, 2, 3, 2, 2, 2, 1)
800	-190.863982	10.090926	10.759637	10.334434	0.456567	ARDL(1, 3, 0, 3, 2, 0, 0)
1174	-186.868987	10.091170	10.927059	10.395555	0.467607	ARDL(1, 2, 3, 1, 2, 2, 2)
2182	-186.873712	10.091401	10.927289	10.395785	0.467484	ARDL(1, 1, 3, 1, 3, 2, 2)
2092	-189.879565	10.091686	10.802192	10.350413	0.460465	ARDL(1, 1, 3, 3, 1, 1, 0)
2407	-189.890190	10.092204	10.802710	10.350931	0.460185	ARDL(1, 1, 2, 2, 1, 2, 1)
2080	-189.896688	10.092521	10.803027	10.351248	0.460014	ARDL(1, 1, 3, 3, 2, 0, 0)
2225	-187.900644	10.092714	10.886809	10.381880	0.465578	ARDL(1, 1, 3, 1, 0, 3, 3)
2860	-192.907388	10.093043	10.678166	10.306113	0.444081	ARDL(1, 1, 0, 3, 1, 1, 0)
1320	-188.913599	10.093346	10.845646	10.367292	0.462920	ARDL(1, 2, 2, 3, 1, 2, 0)
2131	-186.925484	10.093926	10.929815	10.398311	0.466138	ARDL(1, 1, 3, 2, 2, 3, 1)

807	-188.938209	10.094547	10.846847	10.368493	0.462275	ARDL(1, 3, 0, 3, 1, 2, 1)
1576	-189.943335	10.094797	10.805302	10.353524	0.458784	ARDL(1, 2, 1, 3, 1, 2, 0)
2119	-186.945799	10.094917	10.930806	10.399302	0.465609	ARDL(1, 1, 3, 2, 3, 2, 1)
99	-185.949168	10.095081	10.972765	10.414685	0.465516	ARDL(1, 3, 3, 2, 1, 3, 1)
556	-189.960759	10.095647	10.806152	10.354374	0.458324	ARDL(1, 3, 1, 3, 1, 1, 0)
792	-188.962567	10.095735	10.848035	10.369681	0.461636	ARDL(1, 3, 0, 3, 2, 2, 0)
2113	-183.970352	10.096115	11.057387	10.446157	0.460774	ARDL(1, 1, 3, 2, 3, 3, 3)
1048	-186.983877	10.096774	10.932663	10.401159	0.464615	ARDL(1, 2, 3, 3, 2, 2, 0)
1205	-187.987137	10.096934	10.891028	10.386099	0.463318	ARDL(1, 2, 3, 1, 0, 2, 3)
2181	-186.006331	10.097870	10.975553	10.417474	0.464023	ARDL(1, 1, 3, 1, 3, 2, 3)
304	-190.028752	10.098964	10.809469	10.357690	0.456524	ARDL(1, 3, 2, 3, 1, 0, 0)
2068	-187.038602	10.099444	10.935333	10.403829	0.463184	ARDL(1, 1, 3, 3, 2, 3, 0)
292	-187.041410	10.099581	10.935470	10.403966	0.463110	ARDL(1, 3, 2, 3, 1, 3, 0)
165	-186.051923	10.100094	10.977777	10.419698	0.462830	ARDL(1, 3, 3, 1, 1, 2, 3)
2056	-187.073142	10.101129	10.937018	10.405514	0.462279	ARDL(1, 1, 3, 3, 3, 2, 0)
2167	-190.101870	10.102530	10.813036	10.361257	0.454582	ARDL(1, 1, 3, 2, 0, 2, 1)
1109	-185.111059	10.102978	11.022456	10.437802	0.459923	ARDL(1, 2, 3, 2, 2, 2, 3)
280	-187.116170	10.103228	10.939117	10.407612	0.461149	ARDL(1, 3, 2, 3, 2, 2, 0)
1122	-186.124894	10.103653	10.981337	10.423257	0.460914	ARDL(1, 2, 3, 2, 1, 3, 2)
2069	-185.138920	10.104338	11.023815	10.439161	0.459188	ARDL(1, 1, 3, 3, 2, 2, 3)
2596	-190.140755	10.104427	10.814933	10.363154	0.453547	ARDL(1, 1, 1, 3, 1, 3, 0)
2103	-189.147698	10.104766	10.857066	10.378712	0.456752	ARDL(1, 1, 3, 3, 0, 2, 1)
1173	-186.155507	10.105147	10.982830	10.424751	0.460109	ARDL(1, 2, 3, 1, 2, 2, 3)
2856	-192.158943	10.105314	10.732231	10.333603	0.443396	ARDL(1, 1, 0, 3, 1, 2, 0)
2082	-186.172506	10.105976	10.983659	10.425580	0.459661	ARDL(1, 1, 3, 3, 1, 3, 2)
2177	-185.190932	10.106875	11.026352	10.441698	0.457814	ARDL(1, 1, 3, 1, 3, 3, 3)
87	-186.199132	10.107275	10.984958	10.426879	0.458959	ARDL(1, 3, 3, 2, 2, 2, 1)
295	-187.202660	10.107447	10.943336	10.411831	0.458871	ARDL(1, 3, 2, 3, 1, 2, 1)
1060	-187.205815	10.107601	10.943490	10.411985	0.458787	ARDL(1, 2, 3, 3, 1, 3, 0)
615	-189.206520	10.107635	10.859935	10.381581	0.455191	ARDL(1, 3, 1, 2, 1, 2, 1)
811	-190.208959	10.107754	10.818260	10.366481	0.451726	ARDL(1, 3, 0, 3, 1, 1, 1)
360	-189.215463	10.108071	10.860371	10.382018	0.454953	ARDL(1, 3, 2, 2, 1, 2, 0)
559	-190.219009	10.108244	10.818750	10.366971	0.451457	ARDL(1, 3, 1, 3, 1, 0, 1)
163	-187.222115	10.108396	10.944285	10.412780	0.458357	ARDL(1, 3, 3, 1, 1, 3, 1)
2231	-191.239086	10.109224	10.777935	10.352731	0.446532	ARDL(1, 1, 3, 1, 0, 2, 1)
784	-190.240333	10.109285	10.819790	10.368011	0.450886	ARDL(1, 3, 0, 3, 3, 0, 0)
2293	-190.242640	10.109397	10.819903	10.368124	0.450824	ARDL(1, 1, 3, 0, 0, 2, 3)
2348	-191.257396	10.110117	10.778828	10.353625	0.446037	ARDL(1, 1, 2, 3, 1, 1, 0)
2599	-190.258618	10.110176	10.820682	10.368903	0.450396	ARDL(1, 1, 1, 3, 1, 2, 1)
2584	-190.262388	10.110360	10.820866	10.369087	0.450295	ARDL(1, 1, 1, 3, 2, 2, 0)
1062	-186.278476	10.111145	10.988828	10.430749	0.456860	ARDL(1, 2, 3, 3, 1, 2, 2)
48	-189.279488	10.111195	10.863494	10.385141	0.453248	ARDL(1, 3, 3, 3, 1, 0, 0)
1121	-185.284015	10.111415	11.030893	10.446238	0.455347	ARDL(1, 2, 3, 2, 1, 3, 3)
1584	-192.290484	10.111731	10.738648	10.340019	0.439813	ARDL(1, 2, 1, 3, 1, 0, 0)
1187	-188.309803	10.112673	10.906768	10.401839	0.454804	ARDL(1, 2, 3, 1, 1, 3, 1)
2662	-190.310803	10.112722	10.823228	10.371449	0.448995	ARDL(1, 1, 1, 2, 1, 2, 2)
98	-185.326880	10.113506	11.032984	10.448329	0.454207	ARDL(1, 3, 3, 2, 1, 3, 2)
828	-192.330478	10.113682	10.740598	10.341970	0.438719	ARDL(1, 3, 0, 3, 0, 1, 0)
2102	-188.332173	10.113765	10.907859	10.402930	0.454209	ARDL(1, 1, 3, 3, 0, 2, 2)
568	-190.334136	10.113860	10.824366	10.372587	0.448368	ARDL(1, 3, 1, 3, 0, 2, 0)
2343	-189.343043	10.114295	10.866595	10.388241	0.451550	ARDL(1, 1, 2, 3, 1, 2, 1)
150	-186.345571	10.114418	10.992101	10.434022	0.455080	ARDL(1, 3, 3, 1, 2, 2, 2)
101	-185.356738	10.114963	11.034441	10.449786	0.453411	ARDL(1, 3, 3, 2, 1, 2, 3)
161	-185.358745	10.115061	11.034538	10.449884	0.453358	ARDL(1, 3, 3, 1, 1, 3, 3)
2340	-189.360690	10.115156	10.867456	10.389102	0.451078	ARDL(1, 1, 2, 3, 1, 3, 0)
86	-185.361172	10.115179	11.034657	10.450002	0.453293	ARDL(1, 3, 3, 2, 2, 2, 2)
1072	-190.366508	10.115439	10.825945	10.374166	0.447496	ARDL(1, 2, 3, 3, 1, 0, 0)

2081	-185.373008	10.115756	11.035234	10.450580	0.452977	ARDL(1, 1, 3, 3, 1, 3, 3)
2880	-195.374177	10.115814	10.617347	10.298444	0.416237	ARDL(1, 1, 0, 3, 0, 0, 0)
2095	-190.381164	10.116154	10.826660	10.374881	0.447101	ARDL(1, 1, 3, 3, 1, 0, 1)
2120	-188.382575	10.116223	10.910318	10.405389	0.452865	ARDL(1, 1, 3, 2, 3, 2, 0)
35	-185.383435	10.116265	11.035743	10.451088	0.452699	ARDL(1, 3, 3, 3, 1, 3, 1)
1270	-190.386313	10.116406	10.826911	10.375132	0.446962	ARDL(1, 2, 3, 0, 0, 2, 2)
2290	-190.387980	10.116487	10.826992	10.375214	0.446917	ARDL(1, 1, 3, 0, 0, 3, 2)
168	-189.389732	10.116572	10.868872	10.390518	0.450300	ARDL(1, 3, 3, 1, 1, 2, 0)
312	-189.391585	10.116663	10.868963	10.390609	0.450250	ARDL(1, 3, 2, 3, 0, 2, 0)
796	-190.397608	10.116956	10.827462	10.375683	0.446657	ARDL(1, 3, 0, 3, 2, 1, 0)
2648	-191.404922	10.117313	10.786024	10.360821	0.442037	ARDL(1, 1, 1, 2, 2, 2, 0)
2660	-191.408900	10.117507	10.786218	10.361015	0.441928	ARDL(1, 1, 1, 2, 1, 3, 0)
1175	-188.412503	10.117683	10.911777	10.406848	0.452066	ARDL(1, 2, 3, 1, 2, 2, 1)
544	-190.418602	10.117981	10.828486	10.376707	0.446090	ARDL(1, 3, 1, 3, 2, 0, 0)
1840	-193.419070	10.118003	10.703126	10.331073	0.430030	ARDL(1, 2, 0, 3, 1, 0, 0)
2406	-189.419863	10.118042	10.870342	10.391988	0.449491	ARDL(1, 1, 2, 2, 1, 2, 2)
56	-188.427145	10.118397	10.912492	10.407563	0.451674	ARDL(1, 3, 3, 3, 0, 2, 0)
2067	-186.431476	10.118609	10.996292	10.438212	0.452792	ARDL(1, 1, 3, 3, 2, 3, 1)
1328	-191.432315	10.118650	10.787361	10.362157	0.441290	ARDL(1, 2, 2, 3, 1, 0, 0)
1640	-191.432427	10.118655	10.787366	10.362163	0.441287	ARDL(1, 2, 1, 2, 1, 2, 0)
2055	-186.433933	10.118728	10.996412	10.438332	0.452726	ARDL(1, 1, 3, 3, 3, 2, 1)
803	-188.434176	10.118740	10.912835	10.407906	0.451486	ARDL(1, 3, 0, 3, 1, 3, 1)
788	-188.438232	10.118938	10.913033	10.408104	0.451378	ARDL(1, 3, 0, 3, 2, 3, 0)
2114	-185.446420	10.119338	11.038815	10.454161	0.451015	ARDL(1, 1, 3, 2, 3, 3, 2)
2328	-189.447394	10.119385	10.871685	10.393331	0.448751	ARDL(1, 1, 2, 3, 2, 2, 0)
547	-187.454421	10.119728	10.955617	10.424112	0.452184	ARDL(1, 3, 1, 3, 1, 3, 1)
532	-187.454728	10.119743	10.955632	10.424127	0.452176	ARDL(1, 3, 1, 3, 2, 3, 0)
182	-188.460988	10.120048	10.914143	10.409214	0.450768	ARDL(1, 3, 3, 1, 0, 2, 2)
1170	-186.471798	10.120575	10.998259	10.440179	0.451714	ARDL(1, 2, 3, 1, 2, 3, 2)
831	-192.478557	10.120905	10.747822	10.349194	0.434650	ARDL(1, 3, 0, 3, 0, 0, 1)
1047	-186.480204	10.120986	10.998669	10.440589	0.451489	ARDL(1, 2, 3, 3, 2, 2, 1)
23	-185.502480	10.122072	11.041550	10.456895	0.449511	ARDL(1, 3, 3, 3, 2, 2, 1)
612	-189.508037	10.122343	10.874643	10.396289	0.447118	ARDL(1, 3, 1, 2, 1, 3, 0)
1192	-190.508753	10.122378	10.832884	10.381105	0.443649	ARDL(1, 2, 3, 1, 1, 2, 0)
2112	-192.510172	10.122447	10.749364	10.350736	0.433777	ARDL(1, 1, 3, 3, 0, 0, 0)
38	-185.513404	10.122605	11.042083	10.457428	0.449218	ARDL(1, 3, 3, 3, 1, 2, 2)
799	-190.513418	10.122606	10.833111	10.381333	0.443522	ARDL(1, 3, 0, 3, 2, 0, 1)
2162	-188.513905	10.122630	10.916724	10.411795	0.449349	ARDL(1, 1, 3, 2, 0, 3, 2)
2178	-186.516234	10.122743	11.000426	10.442347	0.450524	ARDL(1, 1, 3, 1, 3, 3, 2)

Appendix N: AIC Model Selection Plot for ARDL Specifications, Agriculture Sector

