THE DETERMINANTS OF CO2 EMISSIONS IN UGANDA
(1990-2022)

By

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DECLARATION

I have read the rules of Uganda Martyrs University on plagiarism and hereby state that this work is my own.

It has not been submitted to any other institution for another degree or qualification, either in full or in part.

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APPROVAL

This work on "The impact of urbanization, industrialization and deforestation on CO_2 emissions in Uganda (1990-2022)**"** has been produced under my supervision.

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DEDICATION

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List of Acronyms

ADF: Augmented Dickey-Fuller test

AIC: Akaike Information Criterion

ARDL: Autoregressive Distributed Lag

CEMAC: Central African Economic and Monetary Community

CO2E: Carbon dioxide emissions

EAC: East African Community

ECOWAS: Economic Community of West African States

GDP: Gross Domestic Product

GDPc: Gross Domestic Product per capita

HQC: Hannan-Quinn Information Criterion

LMICs: Low- and Middle-Income Countries

MVA: Manufacturing Value Added

OVB: Omitted Variable Bias

OECD: Organisation for Economic Cooperation and Development

OLS: Ordinary Least Squares

SADC: Southern African Development Community

SDGs: Sustainable Development Goals

SSA: Sub-Saharan Africa

VAR: Vector Autoregressive model

VECM: Vector Error Correlation Model

UP: Urban Population

Abstract

CHAPTER ONE

GENERAL INTRODUCTION

1.0 Introduction

The contemporary discourse on climate change has underscored the critical need to understand the multifaceted contributors to carbon dioxide (CO_2) emissions, which are pivotal drivers of global warming and environmental degradation (Nunes, 2023). Among the various anthropogenic activities, urbanization, industrialization, and deforestation stand out as significant factors influencing CO_2 emissions (Raihan et al., 2022b). This study sought to investigate the impact of these determinants on CO_2 emissions in Uganda, a country experiencing rapid urban growth, industrial expansion, and significant deforestation. By examining the interactions of CO_2 emissions and its determinants in Uganda, the research aimed to contribute to the broader understanding of environmental sustainability in developing countries. This chapter provides a general introduction to the study and includes the background, statement of the problem, objectives of the study, the research hypothesis, and the conceptual framework. Also presented is the significance of the study and the justification for the study. Furthermore, it outlines the scope and limitations of the research, offering a clear understanding of the study's boundaries. The chapter concludes with a brief overview of the subsequent chapters, setting the stage for a comprehensive exploration of the research topic.

1.2 Background to the Study

Globally, CO_2 emissions are a major contributor to the greenhouse effect, leading to global warming and climate change (Kweku et al., 2018). The Intergovernmental Panel on Climate Change (IPCC) reports that industrial activities account for approximately 21% of global CO_2 emissions, while urbanization significantly contributes through increased energy consumption and transportation (IPCC, 2014). The relentless pursuit of economic growth has led to increased fossil fuel consumption and forest clearing, thereby escalating CO_2 emissions (Srivastav and Srivastav, 2015). Urbanization, which involves the expansion of cities and towns, results in higher energy demands for housing, transportation, and infrastructure, further driving up CO_2 emissions (Tanveer et al., 2024). Additionally, deforestation exacerbates the problem by reducing the Earth's capacity to absorb CO_2, as forests act as significant carbon sinks (FAO, 2020). According to the International Energy

Agency (IEA), global CO_2 emissions reached a record high of 36.3 billion metric tons in 2021, reflecting the significant impact of these activities on the global carbon footprint (IEA, 2022). The increase in CO_2 emissions has severe implications for climate stability, with rising temperatures leading to extreme weather events, sea-level rise, and disruptions in ecological systems (Loucks, 2021).

In Sub-Saharan Africa, the trends of urbanization and industrialization are particularly pronounced, with the region experiencing the highest urban growth rate globally at 4.1% annually (Calderon et al., 2019). This rapid urbanization, coupled with industrial expansion, contributes significantly to the region's CO_2 emissions (Akinsola et al., 2022). The expansion of urban areas leads to increased demand for energy, primarily derived from fossil fuels, and heightened transportation needs, both of which contribute to rising CO_2 emissions. Moreover, Sub-Saharan Africa faces severe deforestation issues, losing approximately 3.9 million hectares of forest annually due to agricultural expansion, logging, and infrastructure development (FAO, 2020). The conversion of forest land to agricultural and urban use not only reduces the number of trees available to absorb CO_2 but also releases stored carbon from trees and soil into the atmosphere. This deforestation reduces the region's ability to sequester CO_2, further compounding the environmental challenges (McNicol et al., 2018, Olorunfemi et al., 2022). The interplay of urbanization, industrialization, and deforestation in Sub-Saharan Africa has resulted in increasing CO_2 emissions, posing significant threats to sustainable development and environmental health. The region's vulnerability to climate change impacts, such as droughts, floods, and food insecurity, underscores the need for integrated strategies to manage these drivers of CO_2 emissions.

Uganda exemplifies the environmental challenges associated with urbanization, industrialization, and deforestation in Sub-Saharan Africa. The country has seen its urban population grow from 12% in 2002 to 25% in 2020 (UBOS, 2020). This urban expansion has been accompanied by industrial growth, particularly in the manufacturing and energy sectors, leading to a rise in CO_2 emissions (Appiah et al., 2019). The growth of industries, driven by the need to improve economic outcomes and reduce poverty, has resulted in increased fossil fuel combustion, contributing significantly to national CO_2 emissions. Uganda's deforestation rate is one of the highest globally, with an annual forest cover loss of 2.6%, driven by agricultural activities, charcoal production, and infrastructure development (World Bank, 2023). The reliance on wood fuel for energy and the expansion of agricultural land to feed a growing population have intensified deforestation. The combination of these factors has led to a significant increase in CO_2 emissions, with Uganda emitting approximately 6.1 million metric tons of CO_2 in 2019, a notable rise from previous years (World Bank, 2020). This situation underscores the urgent need to address the environmental impacts of these development activities to ensure sustainable growth. The rising CO_2 emissions pose significant challenges to Uganda's efforts to achieve sustainable development goals, highlighting the need for effective policies to balance economic growth with environmental conservation.

1.2 Statement of the problem

Uganda is experiencing a severe environmental crisis due to escalating CO_2 emissions, significantly impacting public health and development goals (Waaswa and Satognon, 2020). The country's rapid urbanization, industrial expansion, and deforestation have led to a substantial rise in CO_2 emissions, with approximately 6.1 million metric tons emitted in 2019 (World Bank, 2020). This increase, driven by energy demand, industrial activities, and deforestation (Bamwesigye et al., 2020, Bamwesigye et al., 2022), contributes to global climate change and environmental degradation.

While urbanization and industrialization are crucial for economic development, they pose significant environmental risks if not managed sustainably. Deforestation in Uganda, occurring at an annual rate of 2.6% (World Bank, 2023) , reduces the natural absorption of CO_2, further elevating atmospheric CO_2 levels and threatening biodiversity (Nunes, 2023) . The impact of increased CO_2 emissions is profound, contributing to global warming (Hansen et al., 2023), altering weather patterns, and leading to more frequent climate-related events like droughts and floods (Valavanidis, 2022). These changes have direct implications for Uganda's agriculture, water resources, and socio-economic stability, exacerbating food insecurity, health risks, and economic disparities, particularly in rural areas (Otto et al., 2017).

There is a significant knowledge gap regarding the specific contributions of urbanization, industrialization, and deforestation to CO_2 emissions in Uganda. This gap hinders the development of effective, evidence-based policies to mitigate CO_2 emissions and promote sustainable development. This study sought to address these issues by investigating the impact of these determinants on CO_2 emissions in Uganda, providing policymakers with insights needed to develop targeted strategies that balance economic growth with environmental sustainability.

1.3 Objectives of the Study

1.3.1 Main Objective

The main objective of this study was to examine the determinants of CO_2 emissions in Uganda.

1.3.2 Specific Objectives

Specifically, the study sought to:

1. To examine the effect of Urbanisation on CO_2 emissions in Uganda.
2. To assess the effect of industrialisation on CO_2 emissions in Uganda.
3. To analyse the effect of deforestation on CO_2 emissions in Uganda.
4. To analyse the effect of GDP per capita on CO_2 emissions in Uganda.

1.4 Hypotheses of the study

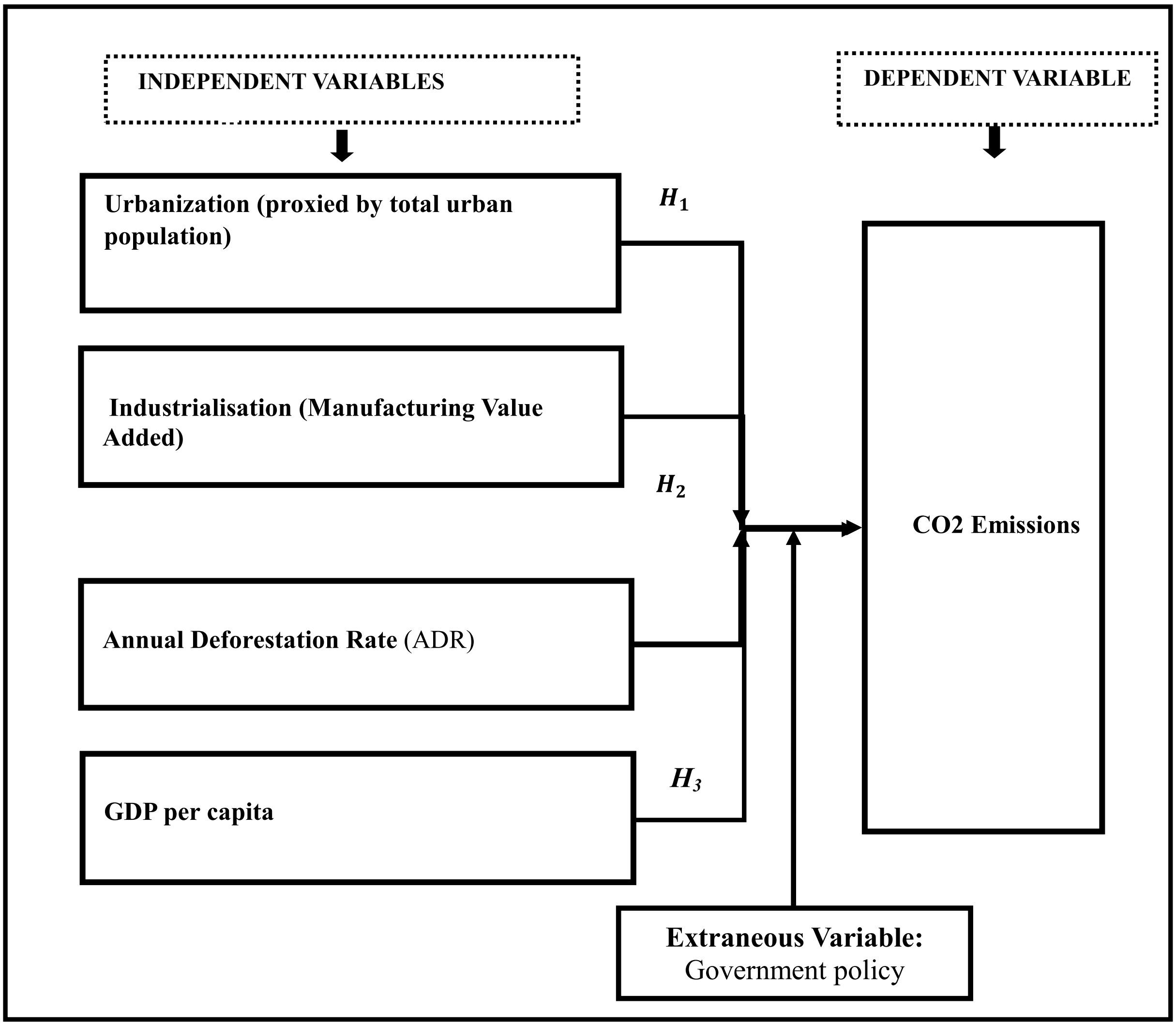
The following hypotheses were proposed to guide thin investigation:

1. There is no significant effect of Urbanisation on CO_2 emissions in Uganda.
2. There is no significant effect of industrialisation on CO_2 emissions in Uganda.
3. There is no significant effect of deforestation on CO_2 emissions in Uganda.
4. There is no significant effect of GDP per capita on CO_2 emissions in Uganda.

1.5 Conceptual Framework

The conceptual framework in Fig. 1.1 delineates the relationships between the independent variables—urbanization, industrialization, and deforestation—and the dependent variable, CO_2 emissions, within the context of Uganda. This framework is designed to illustrate how each independent variable is theorized to influence CO_2 emissions, providing a structured approach to understanding the complex interactions contributing to environmental degradation.

*Figure 1.1**:** The Conceptual Framework for the effect of urbanisation, industrialisation and deforestation on CO2 emissions in Uganda.*



Source: Adopted from Raihan et al. (2022b)

Urbanization is conceptualized as the expansion of urban areas characterized by increased population density and infrastructure development (McGranahan and Satterthwaite, 2014). As urban areas grow, the demand for energy escalates due to heightened residential, commercial, and transportation activities. This increased energy consumption, primarily sourced from fossil fuels, leads to higher CO2 emissions. Urbanization also often results in the conversion of green spaces into built environments, reducing natural carbon sinks and further exacerbating emissions(Zhao et al., 2023). Therefore, in this study, urbanization is expected to significantly elevate CO2 emissions through increased energy use and reduced carbon absorption capacity.

Industrialization is defined as the growth of manufacturing and industrial activities within a country (Scholz, 2018). In Uganda, industrialization involves the expansion of factories, production facilities, and energy-intensive industries. These activities are major sources of CO_2 emissions due to the burning of fossil fuels for energy and the release of greenhouse gases during industrial processes. The development of industrial zones often necessitates substantial energy inputs, contributing to higher emissions. Consequently, industrialization is anticipated to have a direct and substantial impact on CO_2 emissions, reflecting the energy demands and emissions associated with industrial activities.

Deforestation refers to the large-scale clearing of forests for agricultural expansion, logging, and infrastructure development (Kumar et al., 2022). Forests act as significant carbon sinks, absorbing CO_2 from the atmosphere (Chen et al., 2021). When forests are cleared, not only is this absorption capacity lost, but the carbon stored in trees is also released back into the atmosphere, increasing CO_2 levels. In Uganda, deforestation is driven by the need for agricultural land, charcoal production, and infrastructural projects (Twongyirwe et al., 2018). The loss of forest cover leads to a reduction in carbon sequestration and an increase in CO_2 emissions. Therefore, deforestation is expected to have a marked negative effect on CO_2 levels, exacerbating environmental degradation and contributing to climate change.

GDP per capita

The conceptual framework in figure 1.1 posits an Environmental Kuznets Curve (EKC) relationship between GDP per capita and CO_2 emissions. Initially, as GDP per capita increases, CO_2 emissions are expected to rise due to heightened industrial activity, energy consumption, and urbanization, driven by reliance on fossil fuels and expanding infrastructure. However, beyond a certain income threshold, further GDP per capita growth is hypothesized to reduce CO_2 emissions due to technological advancements, stricter environmental regulations, and increased investment in sustainable practices. Thus, the a priori expectation was that CO_2 emissions initially increase with GDP per capita but eventually decline as the economy matures and adopts more sustainable practices.

Extraneous Variables: The framework also recognized the influence of extraneous variables such as energy consumption patterns and GDP per capita. These factors can indirectly affect CO_2 emissions by influencing the scale and efficiency of energy use and economic activities. For instance, higher GDP per capita can lead to increased consumption and industrial activities, thereby elevating CO_2 emissions. Similarly, energy consumption patterns, including the types of energy sources used, play a crucial role in determining the level of emissions.

The conceptual framework of this study posits that urbanization, industrialization, and deforestation are key drivers of CO2 emissions in Uganda. Each of these independent variables contributes to increased emissions through specific mechanisms: urbanization through increased energy demand and reduced green spaces, industrialization through energy-intensive production processes, and deforestation through the loss of carbon sinks and release of stored carbon. Understanding these relationships was essential for developing targeted strategies to mitigate CO2 emissions and promote sustainable development in Uganda. The study aimrd to elucidate these dynamics comprehensively, providing a basis for informed policy-making and environmental management.

1.6 Significance of the study

This study holds significant importance for the academic community by advancing the understanding of the intricate relationships between urbanization, industrialization, deforestation, and CO2 emissions in the context of a developing country like Uganda. It addresses a notable gap in the literature by providing empirical evidence on how these factors specifically contribute to environmental degradation in a rapidly developing economy. While much of the existing research has focused on developed nations, this study offers valuable insights into the dynamics at play in a Sub-Saharan context, specifically Uganda, thereby broadening the scope of environmental and development economics.

The research contributes to the theoretical framework of environmental economics by integrating concepts of sustainable development and ecological impact within the study of economic growth. By examining the distinct and combined effects of urbanization, industrialization, and deforestation, the study enriches the academic discourse on how economic development strategies can be aligned with environmental sustainability goals. This comprehensive approach helps fill a critical void in the literature, where there is a need for more nuanced analyses that account for the multifaceted nature of development activities and their environmental repercussions.

Moreover, the findings of this study will serve as a foundational reference for future academic research. The empirical data and methodological approaches employed can be utilized and built upon by other scholars aiming to explore similar issues in different geographical regions or contexts. This study's insights into the policy implications of its findings can also stimulate scholarly debate and inspire new research directions aimed at formulating innovative solutions to the challenges of balancing economic growth with environmental conservation.

Understanding how urbanization, industrialization, and deforestation each contribute to CO_2 emissions is key for Uganda's sustainable growth. Urbanization and industrialization are essential for economic progress and better living standards, but they come with environmental costs, particularly increased CO_2 emissions. By pinpointing how these activities drive emissions, this study can help policymakers strike a balance between economic development and environmental sustainability.

The insights from this research have significant policy implications. They can guide the creation of targeted strategies to reduce CO_2 emissions in Uganda. For example, recognizing that urbanization increases emissions through higher energy use can lead to adopting energy-efficient technologies and sustainable city planning. Similarly, understanding the impact of industrialization on emissions can result in stricter environmental regulations and promoting cleaner production methods. Addressing the role of deforestation in emissions can inspire more effective forest management and conservation policies.

This study is also significant because it highlights the urgent need for integrated and sustainable development policies that consider both economic growth and environmental conservation. By examining the interplay between urbanization, industrialization, and deforestation, the research underscores the importance of a holistic approach to development planning that can mitigate CO_2 emissions while promoting economic prosperity.

The timing of this research is critical, given the global and local urgency of combating climate change. Uganda's rising CO_2 emissions contribute to global warming and local environmental degradation, which have severe effects on agriculture, health, and socio-economic stability. The findings will add to the global conversation on climate change, offering practical recommendations that could be useful not only in Uganda but also in other developing countries facing similar issues.

1.7 Scope of the study

1.7.1 Content Scope

The scope of this study encompassed an in-depth analysis of the impact of urbanization, industrialization, and deforestation on CO_2 emissions in Uganda. The research aimed to dissect and understand the individual and combined effects of these three critical drivers on the country's CO_2 emissions. By examining urban growth patterns, industrial activities, and deforestation rates, the study provides a comprehensive overview of how these factors contribute to environmental degradation. Additionally, the study explored the socio-economic implications of increased CO_2 emissions and offer policy recommendations to mitigate these impacts while fostering sustainable development.

1.7.2 Time Scope

The temporal scope of this study spanned from 1990 to 2022, covering over three decades of data on urbanization, industrialization, deforestation, and CO_2 emissions in Uganda. This extensive timeframe allowed for a thorough examination of historical trends and patterns, enabling the identification of long-term impacts and changes over time. The study utilized time-series data to analyse the progression and correlation between the independent variables (urbanization, industrialization, and deforestation) and the dependent variable (CO_2 emissions). By covering a substantial period, the research aimed to provide robust insights into how these factors have evolved and influenced CO_2 emissions over time, offering a solid foundation for future policy interventions and sustainable development strategies.

1.7.3 Geographical Scope

The geographical scope of this study was limited to Uganda, a Sub-Saharan African country situated between latitudes 1°S and 4°N, and longitudes 29°E and 35°E. Uganda is bordered by Kenya to the east, South Sudan to the north, the Democratic Republic of the Congo to the west, Rwanda to the southwest, and Tanzania to the south. The country experiences rapid development and significant environmental challenges, making it a pertinent case study. Uganda's pronounced urbanization, burgeoning industrial sector, and high deforestation rates necessitate a detailed examination. The research focused on a macro-level indicator, utilizing macro data on Uganda’s urbanization, industrialization, deforestation rates, and carbon dioxide emissions over the sample period. This approach provided a comprehensive understanding of the temporal variations in CO_2 emissions and the underlying factors driving these emissions on a national scale.

1.7.4 Methodological Scope

This study utilized time series data spanning from 1995 to 2022 to investigate the effect of urbanisation, industrialisation and deforestation on CO_2 emissions in Uganda. The methodological approach encompassed the collection and analysis of historical data to identify trends, patterns, and potential causal relationships between economic activities, energy consumption, industrial expansion, deforestation, and CO_2 emissions. Advanced econometric techniques, including unit root tests, cointegration analysis, and error correction modelling, was utilized to ensure the robustness and reliability of the findings. This comprehensive temporal analysis was meant to provide insights into the dynamics of CO_2 emissions and inform policy recommendations for sustainable environmental management and economic development in Uganda.

1.8 Justification of the Study

The urgency of addressing climate change and environmental degradation necessitated a comprehensive understanding of the factors contributing to CO_2 emissions. This study was justified on several grounds, particularly in the context of Uganda, a developing country experiencing rapid urbanization, industrialization, and deforestation.

Firstly, Uganda's rapid urbanization and industrialization are crucial for its economic development and improvement of living standards. However, these processes are accompanied by significant environmental costs, primarily through increased CO_2 emissions. The current pace of urban growth and industrial expansion necessitates an empirical analysis to identify the specific contributions of these activities to CO_2 emissions. Understanding these contributions is essential for developing targeted strategies that can balance economic growth with environmental sustainability.

Secondly, Uganda's high deforestation rate poses a severe threat to its environmental health and carbon sequestration capacity. Forests play a critical role in absorbing CO_2, and their destruction leads to increased atmospheric CO_2 levels. Given Uganda's annual forest cover loss, it is imperative to quantify the impact of deforestation on CO_2 emissions accurately. This study aimed to fill this gap by providing detailed insights into how deforestation exacerbates CO_2 emissions, thereby informing more effective forest management and conservation policies.

Additionally, the global discourse on climate change often overlooks the specific challenges faced by developing countries. This study contributes to a more nuanced understanding of these challenges by focusing on Uganda. By examining the interplay between urbanization, industrialization, and deforestation in a developing country context, the research highlights the unique environmental dynamics at play. This perspective is crucial for formulating policies that are not only effective but also contextually relevant for developing nations.

Furthermore, the study's temporal scope, spanning three decades, allows for a thorough examination of historical trends and long-term impacts. This extensive timeframe provides a robust foundation for understanding how the relationships between urbanization, industrialization, deforestation, and CO_2 emissions have evolved over time. Such a historical perspective is vital for predicting future trends and crafting long-term strategies to mitigate environmental degradation.

The findings of this study were expected to have significant policy implications. By elucidating the specific impacts of urbanization, industrialization, and deforestation on CO_2 emissions, the research provides policymakers with the evidence needed to develop targeted interventions. These interventions can help mitigate CO_2 emissions while promoting sustainable economic growth. For instance, insights from the study could lead to the adoption of energy-efficient technologies, sustainable urban planning practices, stricter environmental regulations for industries, and more effective forest conservation measures.

Lastly, the study addresses a critical knowledge gap in the literature. While the general relationship between economic activities and CO_2 emissions is well-documented, there is a lack of detailed empirical research focusing on Uganda. This study aimed to bridge this gap, offering valuable contributions to the academic discourse on environmental economics and sustainable development.

1.9 Definition of Major Terms Used in the Study

Urbanization

Urbanization refers to the process by which an increasing proportion of a population migrates from rural to urban areas, leading to the growth and expansion of cities (McGranahan and Satterthwaite, 2014). This phenomenon is typically characterized by the development of infrastructure, increased industrial and commercial activities, and changes in lifestyle. In the context of this study, urbanization is examined as a driver of CO_2 emissions due to the heightened energy consumption and transportation needs associated with expanding urban centres.

Industrialization

Industrialization is defined as the transformation of an economy from primarily agrarian and manual labor-based to one dominated by industry and machine manufacturing(Scholz, 2018) . This process involves the development and expansion of factories, production facilities, and energy-intensive industrial activities. Industrialization is a significant factor in CO_2 emissions as it often relies on the combustion of fossil fuels for energy, leading to the release of greenhouse gases.

Deforestation

Deforestation refers to the large-scale removal or clearing of forests, typically to make way for agricultural activities, logging, or infrastructure development (Kumar et al., 2022). This process results in the loss of trees that act as carbon sinks, thereby reducing the Earth's capacity to absorb CO_2 from the atmosphere. Deforestation contributes to increased CO_2 emissions and is a critical environmental issue examined in this study.

CO_2 Emissions

CO_2 emissions denote the release of carbon dioxide into the atmosphere, primarily from the burning of fossil fuels, deforestation, and various industrial processes (Hung and Skerl, 2020). CO_2 is a major greenhouse gas that contributes to the greenhouse effect, leading to global warming and climate change. This study focuses on CO_2 emissions as the primary measure of environmental impact resulting from urbanization, industrialization, and deforestation.

Carbon Sequestration

Carbon sequestration is the process by which CO_2 is absorbed and stored in natural reservoirs such as forests, soil, and oceans (Hultman, 2020). This process helps to mitigate the effects of greenhouse gas emissions by reducing the amount of CO_2 in the atmosphere. In the context of this study, deforestation's impact on carbon sequestration is a critical factor in understanding changes in CO_2 emissions.

Greenhouse Gases (GHGs)

Greenhouse gases are atmospheric gases that trap heat from the sun, thereby warming the Earth's surface (Kweku et al., 2018). The primary GHGs include carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and fluorinated gases. This study focuses on CO_2 as a key greenhouse gas emitted from urbanization, industrialization, and deforestation activities in Uganda.

Sustainable Development

Sustainable development refers to the organized efforts to meet the needs of the present without compromising the ability of future generations to meet their own needs (Tomislav, 2018, Grunkemeyer and Moss, 2020). This concept integrates economic growth, environmental protection, and social equity. In this study, sustainable development is the overarching goal, seeking to balance economic activities with the preservation of environmental quality.

Fossil Fuels

Fossil fuels are natural energy sources formed from the remains of ancient plants and animals, including coal, oil, and natural gas (Bobrowsky, 2019, Stephanie, 2022). These fuels are burned to produce energy, resulting in the emission of CO2 and other greenhouse gases. The study examines the role of fossil fuel consumption in urbanization and industrialization processes contributing to CO2 emissions in Uganda.

Ecological Footprint

The ecological footprint measures the environmental impact of human activities in terms of the amount of natural resources consumed and the waste produced (Bastianoni et al., 2020). It is a quantitative assessment of the demand placed on the Earth's ecosystems. This study utilizes the concept of the ecological footprint to evaluate the environmental consequences of urbanization, industrialization, and deforestation.

Environmental Degradation

Environmental degradation refers to the deterioration of the environment through the depletion of natural resources, destruction of ecosystems, and pollution (Singh et al., 2022). This process results from human activities such as deforestation, industrial emissions, and urban expansion. The study investigates how these activities contribute to environmental degradation, particularly through increased CO2 emissions.

CHAPTER TWO

LITERATURE REVIEW

2.0 Introduction

The interplay between urbanization, industrialization, and deforestation significantly impacts CO_2 emissions, a major driver of climate change. This chapter reviews the theoretical and empirical literature surrounding these relationships, with a focus on Uganda from 1990 to 2023. By exploring both global and regional studies, the aimed is to provide a comprehensive understanding of how these factors contribute to CO_2 emissions, identify existing research gaps, and suggest areas for further investigation. The structure of this chapter is structured to include a theoretical review that outlines key concepts and theories, an empirical review of studies examining the effects of urbanization, industrialization, and deforestation on CO_2 emissions, and a discussion on the research gap.

2.1 Theoretical Review

The following theoretical frameworks help elucidate the underlying mechanisms and interactions influencing CO_2 emissions. This review explores key theoretical perspectives relevant to understanding CO_2 emissions, focusing on the Environmental Kuznets Curve (EKC) hypothesis, the theory of economic growth and environmental degradation, and structural transformation theory. These theories provide a foundational understanding of how economic development, industrialization, urbanization, and land-use changes impact CO_2 emissions.

2.1.1 Environmental Kuznets Curve (EKC) Hypothesis

The Environmental Kuznets Curve (EKC) hypothesis, first proposed by Grossman and Krueger (1991), suggests an inverted U-shaped relationship between economic development and environmental degradation. Initially, as an economy grows, environmental degradation, including CO_2 emissions, tends to increase due to industrialization and increased consumption. However, after reaching a certain level of income, the trend reverses, and environmental quality improves as the economy matures. This improvement is attributed to increased investments in cleaner technologies, higher environmental awareness, and stricter regulations (Grossman and Krueger, 1991, Panayotou, 1993, Stern, 2004).

2.1.2 Theory of Economic Growth and Environmental Degradation

The theory of economic growth and environmental degradation, articulated by Meadows et al. (1972), posits that economic development often leads to environmental harm, particularly in the early stages of industrialization. Environmental degradation, characterized by pollution, deforestation, and loss of biodiversity, often accompanies rapid economic expansion. According to Meadows et al. (1972), the limits to growth paradigm suggests that unchecked economic growth can lead to severe environmental consequences, potentially undermining long-term sustainability. This perspective highlights the need for integrating environmental considerations into economic planning to achieve sustainable development (Ruggerio, 2021). This theory emphasizes that as economies grow, increased energy consumption and industrial activities result in higher CO_2 emissions. Factors such as urban expansion, industrial production, and transportation contribute significantly to environmental degradation. This perspective highlights the challenge of achieving sustainable development, where economic growth is pursued without exacerbating environmental damage.

2.1.3 Structural Transformation Theory

Structural transformation theory, proposed by Syrquin (1975), focuses on the transition from agriculture-based economies to industrial and service-oriented economies. This transformation often involves significant changes in land use, energy consumption, and industrial activity, all of which can affect CO_2 emissions. As countries industrialize and urbanize, deforestation for agricultural expansion and urban development can lead to increased emissions.

2.1.4 Theory of Sustainable Development

The concept of sustainable development, as defined by the Brundtland Commission (1987), advocates for meeting present needs without compromising the ability of future generations to meet their own needs. This framework emphasizes the interconnectedness of economic, social, and environmental dimensions of development. It underscores the importance of adopting policies that promote economic growth while ensuring environmental sustainability and social equity.

2.1.5 Triangulation of Theories

The interplay between economic growth and environmental degradation in Uganda, particularly in terms of CO_2 emissions, can be effectively understood through a triangulation of three prominent theories: the Environmental Kuznets Curve (EKC) hypothesis, the Economic Growth and Environmental Degradation theory, and the Structural Transformation theory.

The **Environmental Kuznets Curve (EKC)** hypothesis posits that there is an inverted U-shaped relationship between economic growth and environmental degradation. Initially, as a country's economy grows, environmental degradation tends to increase due to urbanization and industrialization. However, past a certain income threshold, further growth can lead to improvements in environmental quality, primarily driven by the adoption of cleaner technologies and stringent environmental regulations. For Uganda, a developing nation, this suggests that CO_2 emissions may rise during the earlier stages of growth as fossil fuels and land use changes, such as deforestation, dominate the economic landscape. However, as Uganda's income levels rise, a transition to more sustainable practices should theoretically occur, leading to a decline in emissions. Nevertheless, the applicability of the EKC in developing countries like Uganda is contentious, with studies indicating that the positive turning point may take longer to achieve or could be impossible without strong governmental policies (Stern, 2018, Stern, 2014).

Complementing the EKC, the **Economic Growth and Environmental Degradation** theory emphasizes that economic progress often correlates with environmental harm, particularly during the early stages of industrial growth. For Uganda, rapid economic expansion has historically led to increased CO_2 emissions, largely fuelled by reliance on fossil fuels and deforestation driven by agricultural expansion and industrial development. This theory highlights that while economic growth can initiate detrimental environmental changes, the severity of this impact is not fixed and can be mitigated through technological advancements and the implementation of regulatory frameworks. The implications for Uganda underscore the urgent need for integrating sustainable practices into economic planning, thereby advocating for cleaner energy sources, improved energy efficiency, and waste management as critical strategies to curb CO_2 emissions (Habiba et al., 2022).

Furthermore, the **Structural Transformation** theory sheds light on the evolution from agriculture-based economies to industrial and service-oriented ones, which often leads to increased industrial activity and deforestation, thereby heightening CO_2 emissions. Uganda's shift from a primarily agrarian economy to an industrial and urbanized economy illustrates this transformation's environmental consequences. The conversion of forested land into industrial and urban areas not only releases stored carbon but also diminishes the carbon sink function of existing forests. This underscores the critical need for policies that advocate for sustainable land use practices and alternative energy solutions, aiming to balance economic development with environmental stewardship.

The triangulation of these theories provides valuable insights into the complex relationship between Uganda's economic growth, urbanization, and CO2 emissions. As Uganda continues its economic transition, it becomes imperative to prioritize sustainable development strategies that reconcile economic advancement with environmental preservation. This involves fostering policies that promote green technologies and responsible land-use practices to mitigate the adverse environmental impacts of structural transformation and economic progress.

2.2 Empirical Review

Empirical studies provide concrete evidence on the relationships between urbanization, industrialization, deforestation, and CO2 emissions. This section reviews relevant studies, with a particular focus on findings from Uganda and other comparable contexts.

2.2.1 Review of Empirical Studies on the Effect of Urbanization (Urban population) on CO2 Emissions

Urbanization, a global phenomenon characterized by the migration of populations from rural to urban areas, has significant implications for environmental sustainability. One critical area of concern is the impact of urbanization on carbon dioxide (CO2) emissions, a primary greenhouse gas contributing to climate change. This literature review examines empirical studies conducted between 2015 and 2024, focusing on the relationship between urbanization and CO2 emissions. The review aims to synthesize key findings, identify patterns, and provide insights into the complexities of urban development and environmental impact.

Several studies have established a direct correlation between urbanization and increased CO2 emissions. For instance, Wang et al. (2014) found that urban expansion in China led to a significant rise in CO2 emissions due to increased energy consumption and transportation needs. Similarly, Fragkias et al. (2017) highlighted that urbanization in developing countries tends to accelerate emissions growth because of the rapid industrialization and urban infrastructure development.

Contrastingly, some research indicates that the relationship between urbanization and CO2 emissions can be non-linear or context-dependent. Research by Liu and Bae (2018) suggests that while urbanization initially increases CO2 emissions, it may eventually lead to emission reductions as cities develop more efficient public transportation systems and implement stricter environmental regulations. This inverted U-shaped relationship, often referred to as the Environmental Kuznets Curve, posits that emissions rise during early stages of urbanization but decline as urban areas mature and adopt sustainable practices.

The role of technological innovation and policy interventions in mitigating CO2 emissions in urban areas has also been a focal point of recent studies. For example, Xu and Lin (2015) demonstrated that cities investing in green technologies and renewable energy sources can significantly curb their CO2 emissions despite ongoing urbanization. Moreover, their study underscores the importance of government policies that promote energy efficiency and sustainable urban planning.

Urban form and structure are crucial factors influencing CO2 emissions, as explored in multiple empirical studies. According to Zheng et al. (2023), compact urban forms, characterized by high-density development and mixed land uses, tend to be more energy-efficient and produce lower per capita CO2 emissions compared to sprawling urban forms. This finding suggests that thoughtful urban design and land-use planning are essential for reducing the carbon footprint of cities.

Recent studies have explored the impact of urbanization on CO2 emissions from a regional perspective, revealing significant geographical variations in these effects. Research by Li and Lin (2015) demonstrated that, in low-income regions, urbanization reduces energy consumption but leads to increased CO2 emissions. Conversely, in middle-/low-income and high-income regions, industrialization decreases energy consumption but raises CO2 emissions, while urbanization substantially boosts both energy consumption and CO2 emissions. For middle-/high-income regions, urbanization does not markedly affect energy consumption but does limit the growth of emissions, whereas industrialization shows minimal impact on both energy consumption and CO2 emissions. Additionally, from a population perspective, urbanization generally enhances energy consumption and raises emissions, with the exception of high-income areas.

In addition to direct emissions, the literature also highlights the role of urbanization in influencing indirect CO2 emissions through changes in consumption patterns and lifestyle. Xu et al. (2024) found that urban residents typically have higher consumption levels and carbon-intensive lifestyles than their rural counterparts, contributing to higher overall emissions. Their study emphasizes the need for promoting sustainable consumption practices alongside urban development.

Urbanization is a significant factor in the increase of CO2 emissions, as it often leads to higher energy consumption, increased transportation needs, and greater waste production. Several studies have examined this relationship, providing valuable insights into how urban growth impacts environmental outcomes. For instance, Lin et al. (2017) conducted a comprehensive study across multiple developing countries, finding a positive correlation between urbanization and CO2 emissions. Their research highlighted the role of increased energy demand and transportation needs as primary contributors to this trend.

A study by Salahuddin et al. (2019) employing second-generation panel regression techniques to estimate the impacts that urbanization and globalization have on CO_2 emissions for a panel of 44 Sub-Saharan Africa (SSA) countries for the period 1984–2016. The estimated coefficient of urbanization was found to positive, statistically significant, and highly consistent across different estimation techniques. Additionally, a causality test performed revealed that urbanization caused emissions.

2.2.2 Review of empirical studies on the effect of industrialisation on CO2 emissions

Industrialization, a driving force of economic development, has been closely linked to increased carbon dioxide (CO2) emissions globally. This review examines empirical studies conducted between 2015 and 2024, focusing on the impact of industrialization on CO2 emissions in various regions, including the OECD, ASEAN, Sub-Saharan Africa, East Africa, and Uganda. The review synthesizes key findings, highlights regional disparities, and discusses the implications of industrial growth on environmental sustainability.

In the OECD countries, extensive research has highlighted the significant impact of industrialization on CO2 emissions. A study by Wang et al. (2015) on the presence of an urbanization-carbon emissions Environmental Kuznets Curve for a panel of the Organization for Economic Co-operation and Development (OECD) countries from 1960 to 2010 using a semi-parametric panel fixed effects regression model found that while industrial activities are a primary source of CO2 emissions, technological advancements and stringent environmental regulations have mitigated some of these effects. They strong evidence for an inverse U-shaped curve relationship between urbanization and carbon emissions, verifying the Environmental Kuznets Curve hypothesis Similarly, Wang et al. (2021) demonstrated that OECD countries have experienced a decoupling of industrial growth and CO2 emissions, attributed to improved energy efficiency and a shift towards service-based economies. However, despite these advancements, the overall emissions from industrial sectors remain substantial.

In the ASEAN region, the rapid pace of energy intensive industrialization has been associated with a marked increase in CO2 emissions (Zafar et al., 2020). According to Hariani et al. (2022)industrial activities in ASEAN countries have led to significant environmental challenges, primarily due to the reliance on fossil fuels and the lack of stringent emission control policies. A study by Roespinoedji et al. (2020) corroborates these findings, highlighting that industrialization in ASEAN is a major contributor to regional CO2 emissions, with energy-intensive industries being particularly problematic. This underscores the need for comprehensive policy frameworks to address the environmental impacts of industrial growth in this region.

Sub-Saharan Africa presents a contrasting scenario where industrialization is still in its nascent stages, yet its impact on CO2 emissions is becoming increasingly evident. Research by (Salahuddin et al., 2019) indicated that while industrialization is crucial for economic development, it has led to a steady rise in CO2 emissions in several Sub-Saharan African countries. Furthermore, Bekhet and Othman (2017) highlighted that the lack of modern technologies and dependence on outdated industrial processes exacerbate the environmental impact. On the other hand, different findings have been reported by Afriyie et al. (2023) in study using panel data from 37 sub-Saharan countries between 1995 and 2017 employed panel cointegration tests and pooled mean group ARDL (PMG-ARDL) techniques, along with the Dumitrescu-Hurlin causality test, to empirically examine the impact of urbanization, economic growth, energy consumption, and industrialization on carbon emissions. Notably, the findings revealed a significantly negative relationship between industrialization and carbon emissions. This indicates that as industrialization progresses in sub-Saharan Africa, carbon emissions do not necessarily increase, and may even decrease, highlighting the potential for sustainable industrial practices. Lin et al. (2015) similarly found that industrial value-added has an inverse and significant relationship with CO_2 emissions, which suggests that there is no evidence that industrialisation increases carbon emissions in Nigeria.

East Africa, a sub-region of Sub-Saharan Africa, has also seen similar trends. A study by Nyambura et al. (2018) found that industrialization in East Africa has resulted in increased CO2 emissions, primarily due to the expansion of manufacturing and energy sectors. A related study by, Sun et al. (2022) found that industrialization led to a reduction in environmental quality in the region through high CO2 emissions.This is further supported by research from Yu et al. (2024), which emphasizes the significant role of industrial activities in driving CO2 emissions in East African countries. All the studies highlight the urgent need for policies promoting energy efficiency and sustainable industrial practices to curb emissions.

Uganda, specifically, has experienced notable industrial growth in recent years, with corresponding environmental impacts. Appiah et al. (2019) conducted a study on the causal relationship between industrialization, energy intensity, economic growth, and carbon dioxide emissions in Uganda for the period from 1990 to 2014. Utilizing the autoregressive distributed lag (ARDL) method, they found that in the long run, a 1% increase in economic growth and industrialization resulted in a 31.1% and 3.2% increase in carbon emissions, respectively. Conversely, a 1% increase in energy intensity led to an 83.9% decrease in emissions. Additionally, the ARDL results indicated that the combined effect of energy intensity, economic progress, and industrialization, when held constant, resulted in a 2.46% reduction in emissions in Uganda. Moreover, Okillong and Luwedde (2023) investigated the effects of industrialization on carbon emissions in Uganda. Their findings, based on the ARDL model, revealed that industrialization has a positive and significant effect on CO2 emissions in the long run. Specifically, a one-unit increase in industrialization resulted in a 0.007632 unit increase in CO2 emissions at a 5 percent significance level. In the short run, industrialization also had a significantly positive effect on CO2 emissions, with a one-unit increase in industrialization leading to a 0.001026 unit increase in emissions at a 5 percent significance level. Furthermore, the NARDL model provided additional insights, showing that positive variations in industrialization significantly increased CO2 emissions both in the short run and long run. Conversely, negative variations in industrialization significantly reduced CO2 emissions in both time frames.

2.2.3 Review of Empirical Studies on the Effect of Deforestation on CO2 Emissions

The effect of deforestation on CO2 emissions has been extensively studied across various regions, including OECD, ASEAN, Sub-Saharan Africa (SSA), East Asia (EA), and Uganda.

Kocoglu et al. (2024) examined the potential of forests to contribute to carbon neutrality. Their research, spanning from 1990 to 2022, analysed data from a global sample of 181 countries to explore the relationship between forest extent and per capita CO2 emissions. They focused on the non-linear effects of economic growth, energy efficiency, and urbanization. By employing dynamic panel threshold and dynamic panel quantile threshold methods, the researchers found that forest extents could serve as a viable alternative to renewable energy and energy efficiency in reducing CO2 emissions. The findings indicated that expanding forest areas significantly impacted mitigating CO2 emissions, thus supporting global environmental improvement efforts.

Raihan et al. (2022a) examined the dynamic impacts of energy use, agricultural land expansion, and deforestation on CO2 emissions in Malaysia, employing a Vector Autoregression (VAR) model. Their findings indicate that deforestation significantly contributes to increased CO2 emissions, emphasizing the urgent need for sustainable land management practices in ASEAN countries. Additionally, a study by Begum et al. (2020) investigated the relationship and dynamic impacts of economic growth and forested area on carbon dioxide (CO2) emissions in Malaysia, covering the period from 1990 to 2016. The researchers utilized the dynamic ordinary least squared (DOLS) approach to analyze the time series data. Focusing on the effect of deforestation, the study found that the long-run coefficient of forested area is negative and significant. Specifically, the results indicate that a reduction of one hectare of forested area leads to an increase of three kilotons of CO2 emissions in Malaysia. This finding underscores the significant adverse impact of deforestation on CO2 emissions, emphasizing the critical need for policy measures aimed at forest conservation, sustainable management, and reforestation to mitigate carbon emissions and support long-term economic growth in Malaysia.

In East Asia, Mighri et al. (2022) examined the impact of urbanization and forest investment on CO2 emissions in China. Employing spatial econometric techniques, the study demonstrated that proper forest management and investments in forest expansion could mitigate CO2 emissions. The findings suggest that while urbanization contributes to deforestation, strategic forest investments can play a pivotal role in carbon abatement.

In the context of OECD countries, Selvanathan et al. (2023) examined the relationship between forestation and CO2 emissions within the context of the Environmental Kuznets Curve (EKC) hypothesis. Their study analysed data from 24 OECD countries over the period from 1990 to 2018. The researchers employed individual-country analysis and panel dynamic analysis to estimate the augmented EKC framework, incorporating the effects of agriculture, forestation, and energy consumption on CO2 emissions. They found that the impact of forest cover on CO2 emissions was mixed at the single-country level. However, the panel fixed-effect results indicated that a 1% increase in forest cover was associated with a 0.63% increase in CO2 emissions. These findings suggest a complex and context-dependent relationship between forestation and CO2 emissions, necessitating nuanced global CO2 emission reduction strategies. Mujtaba et al. (2022) investigated the symmetric and asymmetric impact of economic growth, capital formation, and energy consumption on the environment. Using the CS-ARDL estimation technique, the study found that deforestation, coupled with fossil fuel consumption, exacerbates CO2 emissions. Similarly, Kocoglu et al. (2024) employed a panel data approach along with the cointegration test and the CS-ARDL estimation technique to analyze the role of fossil fuels and renewable energy in environmental sustainability, concluding that deforestation remains a critical factor driving CO2 emissions in OECD countries.

The impact of deforestation on CO2 emissions in SSA has been highlighted by (Sakala et al., 2023), who focused on the effects of charcoal production on carbon cycling in African biomes. Utilizing the LPJ-GUESS model, the study revealed that deforestation for charcoal production significantly alters carbon stock dynamics, leading to increased CO2 emissions. This underscores the need for policies aimed at sustainable charcoal production and forest management in SSA.

Uganda's deforestation and its impact on CO2 emissions have been studied by several researchers. Naturinda et al. (2019) conducted a study to understand the economic consequences of deforestation on carbon emissions in Mabira Forest, Uganda, spanning the years 1995, 2008, and 2018, utilizing satellite imagery, Erdas software, the Invest model, and advanced GIS techniques to model carbon stocks and carbon loss. The analysis revealed a decrease in total carbon stock from 9,150,447.78 Mg C in 1995 to 8,481,434.67 Mg C in 2018, correlating with a reduction in tropical high forest cover from 65.81% to 58.13% over the same period. This deforestation led to increased carbon emissions, with the financial loss escalating from Ush47 trillion between 1995 and 2008 to Ush144 trillion between 2008 and 2018. The findings underscore the importance of incorporating the monetary value of forest carbon sequestration into environmental planning and policy-making.

Furthermore, Olupot et al. (2017) investigated the impact of land use and land cover (LULC) changes on CO2-equivalent (CO2-e) emissions in Uganda's protected areas (PAs). The study focused on several national parks, including Kibale National Park, Mt Elgon National Park, and Bwindi Impenetrable National Park. The research spanned various periods, assessing changes over several decades. The statistical methods included evaluations of biomass and soil carbon stocks, comparing different LULC types such as indigenous tree species, tropical high forests (ITHF), degraded forests (DTHF), grasslands, and maize fields. The findings revealed significant CO2-e sequestration by mature native forests, with deliberate revegetation efforts resulting in a net increase in CO2-e sequestration. Conversely, shifts from ITHF to DTHF or grassland led to substantial CO2-e losses. Soil carbon stocks were highest under maize but were deeper under forest covers, emphasizing the importance of forests in carbon sequestration. The study concluded that changes in LULC away from native types result in net CO2-e losses, highlighting the necessity of conserving PAs for climate change mitigation.

2.2.4 The Effect of GDP per Capita on CO2 Emissions

In the OECD countries, a clear pattern of the Environmental Kuznets Curve (EKC) has been observed, where economic growth initially leads to higher emissions but eventually results in lower emissions as economies transition to more sustainable practices. For instance, a study analysing OECD countries over the period 1992-2018 found that GDP per capita positively affects CO2 emissions, highlighting the initial stages of economic growth where industrial activities dominate (Kutlu and Örün, 2023). However, with technological advancements and stringent environmental policies, these countries have started to witness a decline in emissions, showcasing the inverted U-shaped relationship described by the EKC theory (Le Quéré et al., 2020).

In contrast, the ASEAN region presents a more complex scenario. Rapid industrialization and urbanization have significantly increased CO2 emissions, with economic growth closely tied to energy consumption patterns. A study examining the impact of GDP per capita on environmental degradation in ASEAN countries highlighted that the increase in GDP per capita consistently leads to higher emissions due to heavy reliance on fossil fuels and lack of stringent environmental regulations (Batool et al., 2022). This pattern suggests that ASEAN countries are still in the upward phase of the EKC, where economic growth exacerbates environmental degradation.

The situation in Sub-Saharan Africa (SSA) and East Africa is markedly different due to lower levels of industrialization and economic activity compared to OECD and ASEAN regions. In SSA, the relationship between GDP per capita and CO2 emissions is not as pronounced, primarily due to lower overall emissions and economic activities. However, as these regions continue to develop, the potential for increased emissions is significant if development follows the same carbon-intensive paths as seen in other regions. A study focusing on East Africa found that economic growth is associated with rising emissions, but the absolute levels remain lower compared to more industrialized regions (Gebrechorkos et al., 2023). Similarly, (Namahoro et al., 2021) examined the asymmetric nexus between renewable energy, economic growth, population growth and CO2 emissions in seven East African countries (EACs) using the Common correlated effect means group (CCEMG), nonlinear autoregressive distributed lagged (NARDL), and causality tests for panel data from 1980 to 2016 and found that economic and population growth positively affect CO2 emissions at the regional level.

Specifically, in Uganda, the relationship between GDP per capita and CO2 emissions reflects the broader trends seen in East Africa. Economic activities are still predominantly agrarian, with limited industrialization. However, recent developments in sectors such as manufacturing and services have started to impact emissions. A study on Uganda's economic development and environmental impact noted that while current emissions are relatively low, future economic growth could lead to higher emissions if not managed sustainably (Kiggundu et al., 2022). Therefore, Uganda faces a critical juncture where sustainable development practices must be integrated into its economic growth strategies to avoid the pitfalls of increased CO2 emissions witnessed in other regions.

Furthermore, a by Appiah et al. (2019) study investigated the impact of economic growth on carbon dioxide emissions in Uganda from 1990 to 2014 using an autoregressive distributed lag (ARDL) approach. It found that a 1% increase in economic growth led to increases in carbon emissions by 31.1%. Conversely, a more recent study by (Otim et al., 2022) examining the effects of economic growth, measured by per capita gross domestic product (GDP), on carbon dioxide emissions in Uganda from 1986 to 2018 using the vector error correction model found a significant long-run relationship between GDP per capita and carbon emissions per capita, with an estimated elasticity of 1.856. Their results further indicated unidirectional causality flowing from GDP per capita to carbon dioxide emissions without feedback, supporting the environmental Kuznets curve hypothesis. Additionally, although no causal link between energy consumption per capita and GDP per capita was observed, their findings confirmed that per capita GDP positively influenced carbon dioxide emissions in Uganda.

2.3 The research gaps

The empirical literature reviewed reveals significant insights into the factors influencing CO2 emissions, including GDP per capita, urbanization, industrialization, and deforestation. However, several research gaps remain unaddressed, particularly in the context of developing countries like Uganda.

Firstly, the Environmental Kuznets Curve (EKC) hypothesis has been extensively studied in developed countries, where a clear pattern of initially rising CO2 emissions followed by a decline as economies mature has been observed. This trend, however, is less clear in developing regions. For instance, in the ASEAN countries, rapid industrialization and urbanization continue to drive CO2 emissions upward, indicating that these countries are still in the upward phase of the EKC (Batool et al., 2022). Similarly, in Sub-Saharan Africa and East Africa, the relationship between GDP per capita and CO2 emissions is not as pronounced due to lower levels of industrialization. Nevertheless, as these regions develop, the potential for increased emissions looms large (Gebrechorkos et al., 2023; Namahoro et al., 2021). Specifically, in Uganda, recent studies have highlighted that while current CO2 emissions are relatively low, future economic growth, if not managed sustainably, could lead to higher emissions (Kiggundu et al., 2022). There is a need for more focused research to ascertain whether the EKC hypothesis holds in Uganda and to identify the income threshold at which CO2 emissions might begin to decline.

Secondly, urbanization's impact on CO2 emissions is well-documented in various contexts, yet the relationship can be non-linear and context-dependent. Studies have shown that urbanization initially increases CO2 emissions due to higher energy consumption and transportation needs but may lead to emission reductions as cities develop more efficient public transportation systems and adopt stricter environmental regulations (Liu and Bae, 2018). In Uganda, urbanization is still evolving, and its impact on CO2 emissions requires further empirical investigation to understand the extent to which urban planning and policy interventions can mitigate emissions.

Thirdly, the role of industrialization in driving CO2 emissions varies significantly across regions. In the OECD countries, technological advancements and stringent environmental regulations have helped decouple industrial growth from CO_2 emissions to some extent (Wang et al., 2021). In contrast, the ASEAN region and Sub-Saharan Africa continue to experience rising emissions due to energy-intensive industrial activities and a lack of stringent emission control policies (Zafar et al., 2020; Salahuddin et al., 2019). In Uganda, industrial growth has been associated with increased CO_2 emissions, yet the findings are mixed. Some studies suggest that industrialization significantly increases emissions, while others highlight the potential for sustainable industrial practices to mitigate this impact (Appiah et al., 2019; Okillong and Luwedde, 2023). This disparity indicates a need for more nuanced research to explore the specific conditions under which industrialization can either exacerbate or mitigate CO_2 emissions in Uganda.

Lastly, deforestation's impact on CO_2 emissions is a critical concern, especially in regions like Uganda where forest resources are integral to economic activities. Empirical studies have shown that deforestation significantly contributes to CO_2 emissions, with substantial variations across different contexts (Kocoglu et al., 2024; Raihan et al., 2022a). In Uganda, deforestation has led to significant carbon emissions, highlighting the urgent need for sustainable land management practices (Naturinda et al., 2019; Olupot et al., 2017). However, there is a lack of comprehensive studies that integrate the impact of deforestation with other economic activities such as manufacturing and urbanization in driving CO_2 emissions.

Research Gap Addressed by the Current Study

The current study aims to fill these gaps by investigating the effect of the annual deforestation rate, manufacturing value added, urbanization, and GDP per capita growth on CO_2 emissions in Uganda from 1990 to 2020. By focusing on Uganda, the study will provide insights into the applicability of the EKC hypothesis in a developing country context and identify the critical factors that influence CO_2 emissions during different stages of economic development. It will also explore the non-linear relationship between urbanization and CO_2 emissions, taking into account the specific urbanization patterns and policies in Uganda. Furthermore, the study will examine the impact of industrialization on CO_2 emissions, considering both the potential for sustainable industrial practices and the challenges posed by energy-intensive activities. Lastly, it will integrate the effects of deforestation with other economic activities, providing a holistic understanding of the drivers of CO_2 emissions in Uganda. This comprehensive approach will contribute to the formulation of effective policies aimed at promoting sustainable development and mitigating the adverse environmental impacts of economic growth.

CHAPTER THREE

METHODOLOGY

3.0 Introduction

This chapter explains the methodology which was used in this study to examine the macroeconomic determinants of carbon dioxide emissions (CO2E) in Uganda from 1990 to 2020. It describes the research design, data collection methods, data sources, and analytical techniques used to meet the research objectives and test the hypotheses presented in chapter one. By meticulously detailing each methodological step, this chapter not only enhances the robustness and reliability of the findings but also establishes a comprehensive framework that facilitates replication and validation by other researchers.

3.1 Research design

This study adopted a longitudinal research design to analyse the macroeconomic determinants of CO2 emissions in Uganda from 1990-2020. The choice of the research design wss guided by its suitability and efficiency in examining progressive trends and relationships among time series data over a specified period (Hoffman, 2015).. The longitudinal research design facilitates a consistent and robust analysis of variable behavior over time, enabling precise predictions of long-term effects of various factors on the observed phenomena (Hopwood et al., 2022).

3.2 Data Management

3.2.1 Data Sources and types

Annual time series data pertaining to carbon dioxide emissions and its determinants for the period from 1990 to 2020 were obtained from the Global Forest Watch (accessed at: https://www.globalforestwatch.org/dashboards/country/UGA), World Development Indicators portal, (accessed at: https://databank.worldbank.org/source/world-development-indicators#). Furthermore, for those data points where absence is noted in the World Development Indicators datasets, supplementary values were sourced by consulting various credible macroeconomic data repositories, inclusive of records pertinent to Uganda such as Uganda Bureau of Statistic (UBOS), and Interactive Country Fiches (accessed at: https://dicf.unepgrid.ch/uganda/forest).

3.2.2 Data measurement

In this study, the unit of measure for CO2 emissions, the dependent variable, is thousands of metric tons. This metric quantifies the total emissions released into the atmosphere from various sources, including industrial processes, transportation, and energy production. The primary focus is on how certain economic and demographic factors influence these emissions.

Manufacturing value added, one of the independent variables determining CO2 emissions, is measured as a percentage of GDP. This reflects the contribution of manufacturing activities to the overall economy and is indicative of industrial growth and activity levels. Higher manufacturing output often correlates with increased CO2 emissions due to energy consumption and industrial processes involved in production.

Total urban population, another independent variable, is measured by the number of people residing in urban areas. This metric captures the demographic shift towards urbanization, which typically leads to higher CO2 emissions due to increased demand for transportation, housing, and energy in cities. Urban populations tend to have higher per capita energy consumption and consequently, higher per capita emissions.

GDP per capita, also an independent variable, is measured by dividing the total GDP of the country by its population. This indicator reflects the average economic output per person and serves as a proxy for the standard of living and economic development. Higher GDP per capita often corresponds with greater consumption of goods and services, which can lead to higher CO2 emissions due to increased energy use and industrial activity.

The annual deforestation rate, another critical independent variable, is measured as the percentage reduction in forest area each year. This metric indicates the rate at which forest land is being converted to other uses, such as agriculture or urban development. Deforestation contributes to CO_2 emissions because trees that are cut down release stored carbon dioxide back into the atmosphere. The annual deforestation rate was calculated using the formula:

$$Annual\ deforestation\ rate\ (ADR) = \frac{Forest\ Area_{year1} - Forest\ Area_{year}}{Forest\ Area_{year1}} \qquad 3.1$$

where:

- Forest $Area_{year1}$ refers to the forest area at the initial year.
- Forest $Area_{year}$ is the forest area at the end of the current year.

This formula measures the percentage change in forest area from one year to the next, providing a clear picture of how quickly forest cover is diminishing.

3.2.3 Sample Size and Procedures

In this research will establish the sample size by leveraging the availability of reliable and current data spanning from 1990 to 2020. Rather than employing a rigid mathematical formula, data on the variables of interest from this timeframe will be purposefully selected (Oso and Onen, 2009). This choice yielded a total of 31 annual data points, which we subsequently transformed into quarterly data to bolster the statistical strength of our analysis, resulting in 124 total observations. This approach is consistent with the principles outlined in the Central Limit Theorem, which advocates for a minimum sample size of 30 observations (Lehmann and Casella, 2006) and ideally more than 60 (Groebner *et al*., 2013). By adhering to these statistical guidelines, the researcher will ensure that the model maintains a high level of predictive accuracy and minimized the margin of error associated with a smaller sample size.

3.3 Data Retrieval Methods

The database search/archive retrieval method Cheng and Phillips (2014) will be employed to retrieve relevant data on the study variables. This approach involves secondary data collection, in which the researcher meticulously analyses official datasets from various online sources, including governmental records, statistical databases, and research archives, to identify data relevant to the study variables. Subsequently, the data is organized for analysis and inference generation (Mazhar et al., 2021). An archive retrieval checklist serves as the primary tool in this investigation, acting as a roadmap to guide an in-depth and meaningful examination of documents and datasets pertinent to the research variables. This methodology is chosen due to its effectiveness in structuring the retrieval of secondary data (Rassel et al., 2020), the constraints of time, and my specific interest in investigating the factors contributing to CO2 emissions. The focus will be on monitoring changes over time, identifying trends, and establishing a temporal sequence, all of which necessitate the collection and critical analysis of time-series data relevant to the research goals (Sileyew, 2019).

3.3.1 Data Cleaning and Editing

In order to align the secondary dataset with the goals of this research, a meticulous process of data preparation and refinement will be undertaken. This will involve systematically addressing outliers, accounting for missing values, verifying consistency, and standardizing variable formats. Such steps were critical to guarantee the integrity and suitability of the dataset for performing robust statistical analyses and deriving valid conclusions.

3.3.2 Descriptive Data Analysis

A comprehensive descriptive analysis will be performed on the raw secondary data utilizing EViews 13. This process included the computation of various statistical metrics related to central tendency, variability, and distribution normality. Following the initial description and aggregation of data concerning the research variables, the findings will be organized into a table. Trend graphs will also be drawn(Haneem et al., 2017).

3.4 Model specification

Based on the review of economic literature, the theoretical model for this study is specified based on the Environmental Kuznets Curve (EKC) hypothesis. This is then extended to incorporate the expected determinants of CO2 emissions in Uganda (viz, the annual deforestation rate, manufacturing value added, total urban population. Then by taking natural logs of the variables to linearize and capture elasticities and by including the stochastic error term, the econometric form of the model is developed. This is followed by performing diagnostic tests on the selected variables, Cointegration Test and specification of the Vector Error Correction Model (VECM) to establish the long-term and short-term relationships between CO2 emissions and its determinants in Uganda.

3.4.1 Specification of the Theoretical Model

The Environmental Kuznets Curve (EKC) hypothesis suggests an inverted U-shaped relationship between environmental degradation and economic growth. To model the effect of annual deforestation rate (ADR), manufacturing value added (MVA), urbanization (UP), and GDP per capita (GDPc) on CO2 emissions (CO2), we start with a basic functional form of the EKC hypothesis:

$$E_t = \alpha + \beta Y_t + \gamma Y_t^2 \qquad (3.1)$$

where:

E_t represents the environmental degradation (CO2 emissions) at time t, Y_t represents GDP per capita at time t, Y_t^2 represents the squared term of GDP per capita to capture the inverted U-shaped relationship, α is the intercept term, β and γ are the coefficients to be estimated

Operationalizing and extending the EKC model to include additional determinants of CO2 emission viz; annual deforestation rate (ADR), manufacturing value added (MVA), total urban population (UP), and the stochastic error term we have:

$$CO2_t = \alpha + \delta_1 GDPpc_t + \ \delta_1 (GDPpc_t)^2 + \gamma_1 ADR_t + \gamma_2 MVA_t + \gamma_3 UP_t + \epsilon_t \qquad (3.2)$$

where:

$CO2_t$ is the CO2 emissions at time t, $GDPpc_t$ is the GDP per capita at time t, $(GDPpc_t)^2$ is the squared term of GDP per capita, ADR_t is the annual deforestation rate at time t, MVA_t is the manufacturing value added at time t, UP_t is the level of urbanization at time t, α is the intercept term, δ_1, δ_2, γ_1, γ_2, γ_3 are the coefficients to be estimated and ϵ_t is the error term

To capture elasticities and stabilize variances, a log-log model is developed. Taking natural logarithms of all variables yields:

$$ln(CO2_t) = \alpha + \delta_1 \ln(GDPpc_t) + \delta_2 [\ln(GDPpc_t)]^2 + \gamma_1 \ln(ADR_t) + \gamma_2 \ln(MVA_t) + \gamma_3 \ln(UP_t) + \in_t \qquad (3.3)$$

where:

- ln ($CO2_t$) is the natural log of CO2 emissions at time t,

- $\ln(GDPpc_t)$ is the natural log of GDP per capita at time t,
- $[\ln(GDPpc_t)]^2$ is the squared term of the natural log of GDP per capita to capture the inverted U-shaped relationship,
- $\ln(ADR_t)$ is the natural log of annual deforestation rate at time t,
- $\ln(MVA_t)$ is the natural log of manufacturing value added at time t,
- $\ln(UP_t)$ is the natural log of urbanization at time t,
- α is the intercept term
- $\delta_1, \delta_2, \gamma_1, \gamma_2, \gamma_3$ are the coefficients to be estimated
- ϵ_t is the error term

3.4.2 Variable Description and Justification

The choice of independent variables and their hypothesized effects on CO2 emissions were based on a blend of theoretical insights and empirical evidence. The summary in Table 3.1 outlines the reasoning for each variable and the expected relationship it has with CO2 emissions as the dependent variable.

Table 3.1: Summary of Variables and A Priori Expectations

Variable Name	Definition and Measure	Justification	Sign
GDP per Capita (GDPpc)	The total economic output divided by the population, measured in constant dollars	This variable is included to capture the economic development level, which is hypothesized to follow the Environmental Kuznets Curve (EKC) hypothesis. Studies by Grossman and Krueger (1991) and Panayotou (1993) support this.	Positive then Negative (inverted U-shape)
Annual Deforestation Rate (ADR)	The rate at which forest area is lost annually, measured as a percentage of total forest area	This variable is included because deforestation contributes to CO2 emissions. Supported by studies by Angelsen and Kaimowitz (1999) and Geist and Lambin (2002).	Positive
Manufacturing Value Added (MVA)	The value of manufacturing output minus the value of intermediate inputs, measured as a percentage of GDP	This variable is included to capture the impact of industrial activity on CO2 emissions. Studies by Suri and Chapman (1998) and Zhang (2012) support this.	Positive
Urbanization (UP)	The proportion of the population living in urban areas	This variable is included because urbanization often leads to increased energy consumption and CO2 emissions. Supported by studies by Jones and Kammen (2011) and Chen et al. (2014).	Positive

Source: Author's analysis of theoretical and empirical literature

3.5 Estimation Methods

Given the potential for long-term equilibrium relationships between the variables, a Vector Error Correction Model (VECM) was employed. The Vector Error Correction Model

(VECM) is an advanced multivariate time series model designed to capture both the short-term dynamics and long-term equilibrium relationships among non-stationary variables that are cointegrated. By incorporating an error correction term, the VECM adjusts short-term deviations from the long-term equilibrium, ensuring that the system eventually converges back to equilibrium. This feature makes the VECM particularly valuable for analysing economic and financial time series data, where both long-term relationships and short-term adjustments are crucial.

In this study, the VECM was employed due to the presence of unit roots, a common characteristic in time series data, which indicated that the variables were non-stationary at their levels (I(0)) and at their second differences (I(2)), but stationary at their first differences (I(1)). Since the series were integrated of order one, the VECM was deemed the most appropriate model to simultaneously capture the short-term dynamics and the long-term equilibrium relationships among the variables.

To estimate the VECM, a series of steps were undertaken. First, we tested for stationarity to ensure that none of the series were integrated of order zero (I(0)) or two (I(2)). Next, we determined the optimal number of lags using standard information criteria such as Akaike (AIC), Schwarz (SC), and Hanna-Quinn (HQ). Following this, we performed the Johansen cointegration test to identify the long-term relationships among the variables. Finally, we estimated the VECM based on the established cointegration relationships. This methodological approach ensured a rigorous and systematic analysis of the data, providing robust insights into both the short-term and long-term dynamics of the economic variables under study.

3.5.1 Testing for Unit Root

The Augmented Dickey-Fuller (ADF) test was used to test for the stationarity of the log-transformed study variables. The ADF test extends the Dickey-Fuller test to include higher-order autoregressive processes, thereby correcting for autocorrelation. In this study, the ADF test was undertaken for the log of GDP per capita (GDPpc), annual deforestation rate (ADR), manufacturing value added (MVA), total urban population (UP) and CO2 emissions (CO2). The general form of the ADF test equation for a variable Y is given by:

$$\Delta\ln(Y_y) = \alpha + \beta_t + \gamma \ln(Y_{t-1}) + \sum_{i=1}^{p} \delta_i \Delta \ln(Y_{t-1}) + \epsilon_t \qquad (3.4)$$

where:

$\Delta \ln(Y_t)$ is the first difference of the natural logarithm of the variable Y; α is a constant; β_t is the coefficient on a time trend t; γ is the coefficient of the lagged level of the natural logarithm of Y; δ_i are the coefficients of the lagged first differences of $\ln(Y)_t$; p is the number of lagged first differences included (lag order), and ϵ_t is the error term. The null hypothesis (H_0) of the ADF test is that the series has a unit root (is non-stationary).

Basing on the foregoing equation, the ADF test was conducted for CO2 emissions (CO2), annual deforestation rate (ADR), manufacturing value added (MVA), urban population (UP), and GDP per capita (GDPpc) with the following specifications:

1. ADF test Specification for CO2 emissions

$$\Delta \ln(CO2_t) = \alpha_{CO2,i} + \beta_{CO2}t + \gamma_{CO2}\ln(CO2_{t-1}) + \sum_{i=1}^{p}\delta_{CO2,i}\Delta \ln(CO2_{t-1}) + \epsilon_{CO2,t} \quad (3.5)$$

Where:

$\Delta\ln(CO2_t)$ is the first difference of the natural log of CO2 emissions at time t; α_{CO2} is the intercept term; β_{CO2} is the coefficient on the time trend; γ_{CO2} is the coefficient on the lagged level of the natural log of CO2 emissions; $\delta_{CO2,\,i}$ are the coefficients on the lagged differences of the natural log of CO2 emissions and $\epsilon_{CO2,\,t}$ is the error term

2. ADF test specification for the Annual Deforestation Rate (ADR):

$$\Delta \ln(ADR_t) = \alpha_{ADR,i} + \beta_{ADR}t + \gamma_{ADR}\ln(ADR_{t-1}) + \sum_{i=1}^{p}\delta_{ADR,i}\Delta \ln(ADR_{t-1}) + \epsilon_{ADR,t} \quad (3.6)$$

3. ADF test specification for manufacturing value added (MVA):

$$\Delta \ln(MVA_t) = \alpha_{MVA,i} + \beta_{MVA}t + \gamma_{MVA}\ln(MVA_{t-1}) + \sum_{i=1}^{p}\delta_{MVA,i}\Delta \ln(MVA_{t-1}) + \epsilon_{MVA,t} \quad (3.7)$$

4. ADF test specification for total urban population (UP):

$$\Delta \ln(UP_t) = \alpha_{UP,i} + \beta_{UP}t + \gamma_{UP}\ln(UP_{t-1}) + \sum_{i=1}^{p}\delta_{UP,i}\Delta \ln(UP_{t-1}) + \epsilon_{UP,t} \quad (3.8)$$

5. ADF unit root test specification for GDP per Capita (GDPpc):

$$\Delta \ln(GDPpc_t) = \alpha_{GDPpc,i} + \beta_{GDPpc}t + \gamma_{GDPpc} \ln(GDPpc_{t-1}) + \sum_{i=1}^{p} \delta_{GDPpc,i}\Delta \ln(GDPpc_{t-1}) + \epsilon_{GDPpc,t} \quad (3.9)$$

By taking the first differences of variables that were integrated of order one (I(1))—ensuring they were neither integrated of order zero (I(0)) nor order two (I(2))—the resulting stationary series provided a solid foundation for estimating the Vector Error Correction Model (VECM). This approach ensured that the variables used in the VECM were stationary, which was a critical requirement for producing robust and consistent estimates of the population parameters. Stationarity in the first-differenced series allowed the VECM to effectively capture both the short-term dynamics and long-term equilibrium relationships among the variables, leading to reliable and meaningful econometric analysis.

3.5.2 Optimal Lag Length determination

In order to identify the most suitable criterion for determining the optimal lag length in the model, unrestricted VAR estimates were generated under the premise that the series exhibited no co-integration. Adhering to established selection criteria, specifically IC(p) as initially proposed by Vahid and Engle (1993) and cited in the work of Carrasco Gutierrez et al. (2009), our estimation process comprised multiple steps. Initially, a VAR analysis was conducted using the level forms of the endogenous variables, with an initial arbitrary selection of lags set to reflect the data's temporal characteristics, such as four lags for quarterly datasets. Subsequently, the optimal lag length, denoted as p, was estimated utilizing conventional information criteria including Akaike (AIC), Schwarz (SC), and Hannan-Quinn (HQ) as recommended by Almeshqab et al. (2019). The lag length that minimized these information criteria was ultimately selected for the VAR in levels. In conclusion, following the determination of the optimal lag length, the Johansen cointegration test was applied, leading to the estimation of the final Vector Error Correction Model (VECM). This structured methodology ensured that the selection of lag length was performed based on stringent statistical principles, establishing a solid groundwork for subsequent analyses.

3.5.3 The Johansen cointegration Test

This phase included estimating the Johansen cointegration test, developed by Johansen and Juselius (1990), to assess the existence of long-run cointegrating relationships among the I(1) variables. The focus of this test is on the levels of the series rather than their first differences. In this analysis, the variables were transformed using natural logarithms, which were then employed to explore the long-run relationships. According to Johansen and Juselius, the multivariate cointegration model is represented as follows:

$$\Delta y_t = \prod y_{t-1} + \sum_{i=1}^{P-1} \Gamma_i \Delta y_{t-1} + u_t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. \quad (3.10)$$

Where $\mathbf{\Pi}$ and $\mathbf{\Gamma}_i$ are coefficient matrices, Δ is the difference operator, and P is the lag order selected based on the Schwarz Bayesian Criterion (SBC). The Johansen and Juselius cointegration test involve two likelihood ratio tests: the trace test and the maximum eigenvalue test, which are calculated as follows:

$$Tr = -T\sum_{i=r+1}^{n} \ln(1-\hat{\lambda}_i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3.11)$$

$$Max\lambda = -Tln\left(1-\hat{\lambda}_{r+1}\right) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3.12)$$

Where $\hat{\lambda}$ represents the estimated eigenvalue of the characteristic roots and T denotes the sample size. In the trace test, the null hypothesis (H_0) assesses the number of cointegrating vectors r against the alternative hypothesis (H_1) of n cointegrating vectors. Similarly, in the maximum eigenvalue test, the null hypothesis evaluates the number of cointegrating vectors r against the alternative hypothesis (H_1) of r+1 cointegrating vectors. The presence of one or more cointegrating vectors indicates long-run equilibrium relationships among the variables. By conducting the cointegration test on only the level form of the variables and not on their first difference, we tested the null of non-existence of a long-run relationship ($\boldsymbol{H_0}$:$\boldsymbol{b_i} = \boldsymbol{b_j}$= **0)** against the alternative hypothesis that a long run relationship exists ($\boldsymbol{H_1}$**:** $\boldsymbol{b_i} \neq \boldsymbol{b_j} \neq \mathbf{0}$).

3.5.4 Estimation of the VECM

To capture both the long run and short run dynamics between the series, we adopted the VECM approach by modifying equation 3.11 above basing on Pesaran and Shin (1996,2001) to generate to a general equation. The general form of the VECM with CO2 emissions as the dependent variable and independent variables including the annual deforestation rate (ADR), manufacturing value added (MVA), total urban population (UP) and GDP per capita (GDPpc) was specified as follows:

First, **estimation of the Cointegrating Equation** was done to identify the long-run equilibrium relationship between the variables using the Johansen cointegration test. The equation was of the following form:

$$ln(CO2_t) = \alpha + \delta_1 \ln(GDPpc_t) + \delta_2[\ln(GDPpc_t)]^2 + \gamma_1 \ln(ADR_t) + \gamma_2 \ln(MVA_t) + \gamma_3 \ln(UP_t) + \epsilon_t \quad (3.13)$$

Then the residuals from the cointegrating equation were then used to specify the VECM model with an error correction term (ECT) for the log-transformed variables, which reflects deviations from the long-term equilibrium. The ECT specification for CO2 emissions was of the form:

$$\begin{aligned}\Delta \ln(CO2_t) = \lambda_1(\ln(CO2_{t-1}) - \alpha - \delta_1 \ln(GDPpc_t) - \delta_2[\ln(GDPpc_t)]^2 - \gamma_1 \ln(ADR_t) \\ - \gamma_2 \ln(MVA_t) - \gamma_3 \ln(UP_t) + \sum_{i=1}^{p-1} \phi_{1i}\, \Delta\ln(CO2_{t-1}) \\ + \sum_{i=1}^{p-1} \phi_{2i}\, \Delta\ln(GDPpc_{t-1}) + \sum_{i=1}^{p-1} \phi_{3i} \Delta[\ln(GDPpc_{t-1})]^2 \\ + \sum_{i=1}^{p-1} \phi_{4i}\, \Delta\ln(ADR_{t-1}) + \sum_{i=1}^{p-1} \phi_{5i}\, \Delta\ln(MVA_{t-1}) \\ + \sum_{i=1}^{p-1} \phi_{6i}\, \Delta\ln(UP_{t-1}) + \epsilon_{1t} \quad (3.14)\end{aligned}$$

where:

- $\Delta\ln(CO2_t)$ is the first difference of the natural log of CO2 emissions at time t
- λ_1 is the adjustment coefficient indicating the speed of adjustment to the long-run equilibrium
- The term **$(\ln(CO2_{t-1}))-\alpha-\delta_1\ln(GDPpc_{t-1})-\delta_2[\ln(GDPpc_{t-1})]^2-\gamma_1\ln(ADR_{t-1})-\gamma_2\ln(MVA_{t-1})-\gamma_3\ln(UP_{t-1}))$** is the error correction term (ECT)
- ϕ_{1i}, ϕ_{2i}, ϕ_{3i}, ϕ_{4i}, ϕ_{5i}, ϕ_{6i} are the short-run coefficients for the lagged differences of the respective log-transformed variables.
- ϵ_{1t} is the error term

The the detailed specification of the VECM for the determinants of CO2 emissions was as follows:

1. **GDP per capita (GDPpc)**

$$\Delta \ln(GDPpc_t) = \lambda_2 ECT_t + \sum_{i=1}^{p-1} \psi_{1i} \Delta\ln(CO2_{t-1}) + \sum_{i=1}^{p-1} \psi_{2i} \Delta\ln(GDPpc_{t-1}) + \sum_{i=1}^{p-1} \psi_{3i} \Delta[\ln(GDPpc_{t-1})]^2 + \sum_{i=1}^{p-1} \psi_{4i} \Delta\ln(ADR_{t-1}) + \sum_{i=1}^{p-1} \psi_{5i} \Delta\ln(MVA_{t-1}) + \sum_{i=1}^{p-1} \psi_{6i} \Delta\ln(UP_{t-1}) + \epsilon_{2t} \quad (3.15)$$

2. Squared GDP per Capita [(GDPpc)^2]

$$\Delta[\ln(GDPpc_{t-1})]^2 = \lambda_3 ECT_t + \sum_{i=1}^{p-1} \theta_{1i} \Delta\ln(CO2_{t-1}) + \sum_{i=1}^{p-1} \theta_{2i} \Delta\ln(GDPpc_{t-1}) + \sum_{i=1}^{p-1} \theta_{3i} \Delta[\ln(GDPpc_{t-1})]^2 + \sum_{i=1}^{p-1} \theta_{4i} \Delta\ln(ADR_{t-1}) + \sum_{i=1}^{p-1} \theta_{5i} \Delta\ln(MVA_{t-1}) + \sum_{i=1}^{p-1} \theta_{6i} \Delta\ln(UP_{t-1}) + \epsilon_{3t} \quad (3.16)$$

3. The Annual Deforestation Rate (ADR)

$$\Delta\ln(ADR_t) = \lambda_4 ECT_t + \sum_{i=1}^{p-1} \eta_{1i} \Delta\ln(CO2_{t-1}) + \sum_{i=1}^{p-1} \eta_{2i} \Delta\ln(GDPpc_{t-1}) + \sum_{i=1}^{p-1} \eta_{3i} \Delta[\ln(GDPpc_{t-1})]^2 + \sum_{i=1}^{p-1} \eta_{4i} \Delta\ln(ADR_{t-1}) + \sum_{i=1}^{p-1} \eta_{5i} \Delta\ln(MVA_{t-1}) + \sum_{i=1}^{p-1} \eta_{6i} \Delta\ln(UP_{t-1}) + \epsilon_{4t} \quad (3.17)$$

4. Manufacturing Value Added (MVA)- a proxy for industrialization

$$\Delta\ln(MVA_t) = \lambda_5 ECT_t + \sum_{i=1}^{p-1} \mu_{1i} \Delta\ln(CO2_{t-1}) + \sum_{i=1}^{p-1} \mu_{2i} \Delta\ln(GDPpc_{t-1}) + \sum_{i=1}^{p-1} \mu_{3i} \Delta[\ln(GDPpc_{t-1})]^2 + \sum_{i=1}^{p-1} \mu_{4i} \Delta\ln(ADR_{t-1}) + \sum_{i=1}^{p-1} \mu_{5i} \Delta\ln(MVA_{t-1}) + \sum_{i=1}^{p-1} \mu_{6i} \Delta\ln(UP_{t-1}) + \epsilon_{5t} \quad (3.18)$$

5. Urban population (UP)- a proxy for urbanization

$$\Delta\ln(UP_t) = \lambda_6 ECT_t + \sum_{i=1}^{p-1} \sigma_{1i}\,\Delta\ln(CO2_{t-1}) + \sum_{i=1}^{p-1} \sigma_{2i}\,\Delta\ln(GDPpc_{t-1}) + \sum_{i=1}^{p-1} \sigma_{3i}\Delta[\ln(GDPpc_{t-1})]^2 + \sum_{i=1}^{p-1} \sigma_{4i}\,\Delta\ln(ADR_{t-1}) + \sum_{i=1}^{p-1} \sigma_{5i}\,\Delta\ln(MVA_{t-1}) + \sum_{i=1}^{p-1} \sigma_{6i}\,\Delta\ln(UP_{t-1}) + \epsilon_{6t} \quad (3.19)$$

3.6 Diagnostic Tests

3.6.1 Test for Normality

The current study employed the Jarque-Bera statistic to test for normality in the data distribution. This statistic evaluates whether the sample data follows a normal distribution by comparing the skewness and kurtosis of the series to those of a normal distribution. According to (Gujarati, 2004), the test statistic is calculated using the formula:

$$JB = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (3.20)$$

Where n=sample size, S=skewness coefficient, K=kurtosis coefficient. The statistic follows a chi-square distribution with 2 *df*.

The null hypothesis posits that the data follows a normal distribution, whereas the alternative hypothesis asserts that the data does not. Thus, the null hypothesis of normality is rejected if the computed p-value of the Jarque-Bera (JB) statistic is less than the 5% significance level. Testing for normality is crucial in regression analysis because many statistical tests assume that the disturbances are normally distributed. The Jarque-Bera test helps validate this assumption, thereby ensuring the reliability of the regression results.

3.6.2 Multicollinearity Test

The Variance Inflation Factor (VIF) test will be used in this study to detect multicollinearity in the regression model. Multicollinearity occurs when there is a perfect or near-perfect linear relationship among the explanatory variables, leading to inflated standard errors of the estimated coefficients. Although multicollinearity does not affect the Best Linear Unbiased Estimators (BLUE) properties of OLS estimates, it can significantly impact the precision of the coefficient estimates.

3.7 Residual diagnostic tests

To ascertain the appropriateness of the adopted model for the data spanning the sample period, several diagnostic tests will be conducted on the residuals.

3.7.1 Coefficient of determination (R^2).

The R-squared (R^2) statistic will be utilized to assess the goodness of fit of the regression model in predicting the dependent variable within the sample. Theoretically, an R^2 value of one indicates a perfect fit, while a value of zero indicates no explanatory power of the model. R^2 thus represents the proportion of variance in the dependent variable that is explained by the independent variables. It provides a measure of how well the regression model captures the overall variability of the dependent variable.

3.7.2 The Jarque-Bera Test for normality

To test the normality of residuals, the Jarque-Bera normality test will be employed at a 95% confidence level and a 5% significance level. Non-normality in the residuals indicates the presence of outliers or a general lack of model fit. The null hypothesis posits that the data is normally distributed, while the alternative hypothesis asserts non-normality. The decision criterion will involve to rejecting the null hypothesis if the P-value of the Jarque-Bera statistic is less than 5%, and to fail to reject it if the P-value exceeded 5%.

3.7.3 Test for Serial Correlation

This study will use the Breusch-Godfrey serial correlation Lagrange Multiplier test because according to (Gujarati and Porter, 2009), it is much more general in that it allows for both AR and MA error structures as well as the presence of a lagged regressand as an explanatory variable. This makes it more suitable for the VECM approach adopted in this study.

The null hypothesis ($\mathbf{H_0}$) to be tested is that there is no serial correlation of any order against the alternative that there is serial correlation in the model's residuals. Normally, when the p-value is less than the critical value at 5% level of significance, the null can rejected, and where the p-value is greater than 5%, we fail to reject the null hypothesis.

3.7.4 Heteroskedasticity Test

According to the assumption of classical linear regression, the variance of the error term must be constant (Homoscedasticity) for all observations, $\mathbf{E}\ (\mathcal{E}_j^2) = \boldsymbol{\sigma^2}$. If the error terms do not have constant variance, they are said to be heteroscedastic. This is undesirable for a good model. This study adopts the Breusch-Pagan-Godfrey heteroskedasticity test regressing squared residuals on the original regressors assuming the **null hypothesis** that the series are not heteroscedastic against the **alternative** that they are heteroscedastic. The decision criterion is that where the probability value of the F-statistic is less than the critical value at

5%, we reject the null and concluded that the series are heteroscedastic. But where the probability value is greater than 0.05 at 5% level of significance, we fail to reject the null hypothesis and concluded that there was no presence of heteroskedasticity. Similarly, where the chi-square probability of the observed R-squared is less than 5%, we reject the null hypothesis; otherwise, we fail to reject the null and concluded that the series are homoscedastic.

CHAPTER FOUR

DATA ANALYSIS AND PRESENTATION

4.0 Introduction

This chapter presents the findings from the various tests and analyses conducted on the data in relation to the objectives and hypotheses of the study. The presentation of findings is systematically structured, beginning with the results from the descriptive analysis of the variables under study, including trend analysis. This is followed by the results from bivariate analysis and pre-estimation diagnostic tests, such as tests for normality, stationarity, and multicollinearity. Subsequently, the chapter presents the estimation of the normalized coefficients, providing insights into the long-term relationships among the variables. The chapter also includes the estimation and interpretation of the Vector Error Correction Model (VECM), highlighting both short-term dynamics and long-term equilibrium adjustments. Each section is detailed to ensure a comprehensive understanding of the data analysis process and the robustness of the results. The interpretation of findings and subsequent discussion aligns with the theoretical framework and empirical literature reviewed in earlier chapters, providing a thorough understanding of the results in the context of the study's objectives. This structured approach ensures clarity and coherence in presenting the study's key findings and their implications, ultimately laying a firm pedestal for the drawing of conclusions and policy recommendations on the macroeconomic determinants of CO2 emissions in Uganda.

4.1 Descriptive Analysis

4.1.1 Descriptive Statistics

Table 4. 1: Descriptive statistics

STATISTIC	CARCONDIOXIDE EMISSIONS (CO_2)	ANNUAL DEFORESTATION RATE (ADR)	MANUFACTURING VALUE ADDED (MVA)	TOTAL URBAN POPULATION (UP)	GDP PER CAPITA (GDPC)
Mean	2798.632	1.412144	10.45911	5376547.	483.7506
Median	2230.000	1.395232	7.354144	4695306.	330.6029
Maximum	6130.000	1.733953	17.14687	11414209	897.5097
Minimum	730.0000	1.154040	5.341026	1922173.	151.9765
Std. Dev.	1862.172	0.175995	4.696578	2809438.	278.2825
Skewness	0.493956	0.250444	0.409289	0.634780	0.354538
Kurtosis	1.775481	1.844372	1.289229	2.252321	1.306647
Jarque-Bera	3.197411	2.049052	4.645877	2.803958	4.353215
Probability	0.202158	0.358966	0.097985	0.246109	0.113426
Sum	86757.60	43.77645	324.2324	1.67E+08	14996.27
Sum Sq. Dev.	1.04E+08	0.929225	661.7353	2.37E+14	2323235.
Observations	31	31	31	31	31

Source: Author's analysis of World Bank data

The descriptive statistics in Table 4.1 provide a comprehensive summary of the key variables under investigation in this study, which include carbon dioxide (CO2) emissions, annual deforestation rate (ADR), manufacturing value added (MVA), total urban population (UP), and GDP per capita (GDPC). These statistics offer insights into the central tendency, dispersion, and distributional characteristics of the data over the study period.

The mean value of CO_2 emissions is 2798.632, with a median of 2230.000, indicating that the data are right-skewed, which is further supported by the positive skewness of 0.493956. The high standard deviation of 1862.172 highlights considerable variability in CO_2 emissions. This skewness and variability suggest that while most observations are concentrated around the lower values, there are some significantly higher emissions data points, likely corresponding to periods of intensified industrial activity or urbanization. In comparison to related empirical literature, similar patterns of high variability in CO_2 emissions have been observed in other developing economies where industrial growth and urbanization are uneven and sporadic.

For ADR, the mean is 1.412144 with a median of 1.395232, showing a slight right skewness of 0.250444 and a low standard deviation of 0.175995. This indicates a relatively stable rate of deforestation over the period, though with slight fluctuations. The low kurtosis of 1.844372 suggests fewer extreme deforestation rates compared to a normal distribution. Empirical studies in regions with high forest cover and agricultural pressures often report similar patterns, highlighting the consistent yet slightly increasing deforestation trends due to expanding agricultural activities.

The MVA shows a mean of 10.45911 and a median of 7.354144, with a higher maximum value of 17.14687 and a minimum of 5.341026. The positive skewness of 0.409289 and low kurtosis of 1.289229 indicate a right-skewed distribution with moderate variability (standard deviation of 4.696578). These statistics imply that manufacturing activities are expanding, though they vary significantly year to year. This aligns with findings in other developing economies where industrial sectors are growing but not uniformly due to fluctuations in economic policies and investment levels.

The UP has a mean of 5376547 and a median of 4695306, with significant variability as indicated by the standard deviation of 2809438. The positive skewness of 0.634780 and kurtosis of 2.252321 suggest a distribution skewed to the right with some concentration around the lower values, yet some much higher values, reflecting periods of rapid urban population growth. This pattern is consistent with urbanization trends in developing countries where migration to urban areas can accelerate quickly due to economic opportunities.

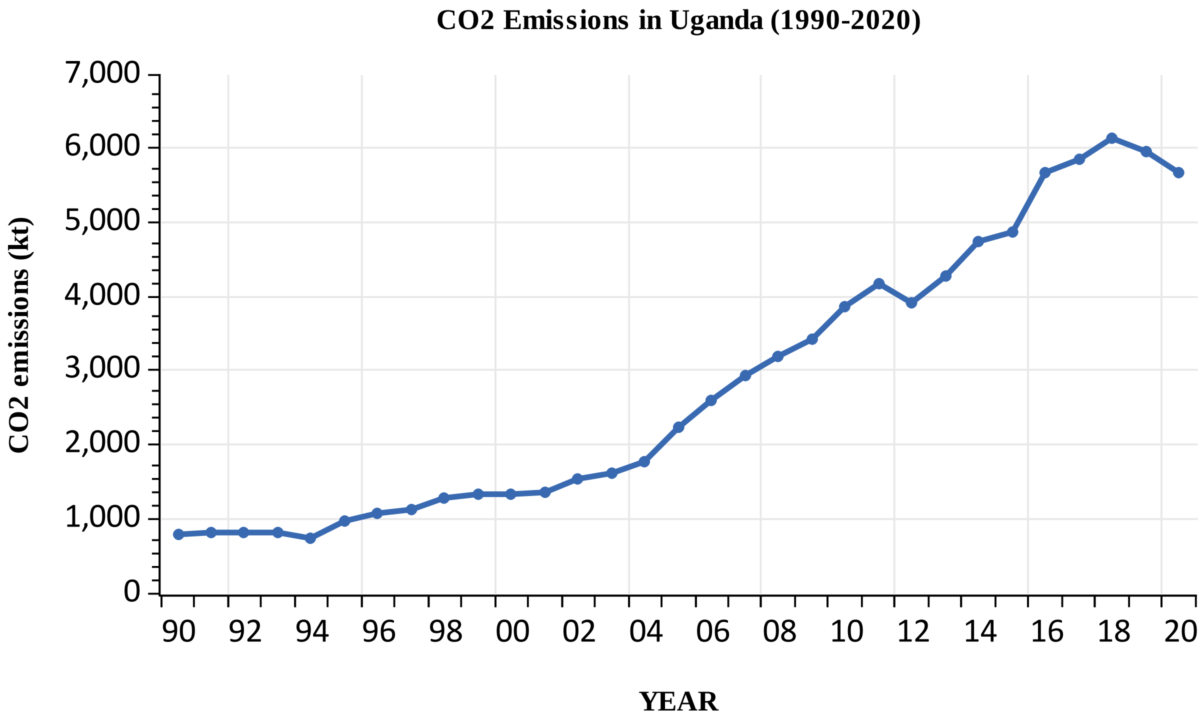
The GDPC displays a mean of 483.7506 and a median of 330.6029, with a maximum of 897.5097 and a minimum of 151.9765. The standard deviation of 278.2825 points to considerable variation in GDP per capita. The positive skewness of 0.354538 and low kurtosis of 1.306647 suggest a right-skewed and flat distribution. This indicates that while there has been significant economic growth, the distribution of income is uneven, which is a common scenario in developing economies transitioning towards higher income levels.

4.1.2 Trends of Variables

4.1.2.1 Trend of CO2 emissions in Uganda 1990-2020

Figure 4.1 below shows the trend of Carbon dioxide emissions in Uganda from 1990 to 2020.

Figure 4. 1: The trend of CO_2 emissions in Uganda, 1990-2020.



Source: Author's analysis of World Bank data

The trend of CO2 emissions in Uganda from 1990 to 2020 reveals a significant and mostly consistent increase over the three decades, with a few notable fluctuations. In 1990, CO2 emissions were relatively low at 790.0 metric tons, indicative of a less industrialized and more agrarian economy with limited fossil fuel consumption. This level remained relatively stable until 1994, where emissions experienced a slight drop to 730.0 metric tons. This drop could be attributed to economic or policy factors that temporarily reduced industrial activity or improved efficiency in energy use.

From 1995 onwards, CO2 emissions began to rise sharply, reaching 960.0 metric tons and continuing to increase almost every year. By 1996, emissions had climbed to 1070.0 metric tons, and by 1997, they had increased further to 1130.0 metric tons. This period marks the beginning of significant economic growth and industrialization in Uganda, driven by both domestic and foreign investments in manufacturing and other energy-intensive sectors.

The late 1990s and early 2000s saw a continued upward trajectory, with emissions reaching 1320.0 metric tons in 1999 and 1350.0 metric tons in 2001. The implementation of infrastructure projects and the expansion of urban areas likely contributed to this growth. By 2002, emissions had risen to 1540.0 metric tons, reflecting the increasing use of fossil fuels in transportation, industrial processes, and electricity generation.

The mid-2000s witnessed a more rapid increase in emissions. By 2005, CO_2 emissions had surged to 2230.0 metric tons, doubling from the levels seen a decade earlier. This sharp rise can be attributed to accelerated industrialization and urbanization, coupled with the expansion of the manufacturing sector and increased energy consumption from both commercial and residential sources.

In the following years, emissions continued to escalate. By 2008, emissions had reached 3180.0 metric tons, and by 2010, they had grown to 3850.0 metric tons. The early 2010s continued this trend, with emissions peaking at 4270.0 metric tons in 2013. This period was characterized by further industrial expansion, increased vehicle usage, and a growing urban population, all contributing to higher fossil fuel consumption.

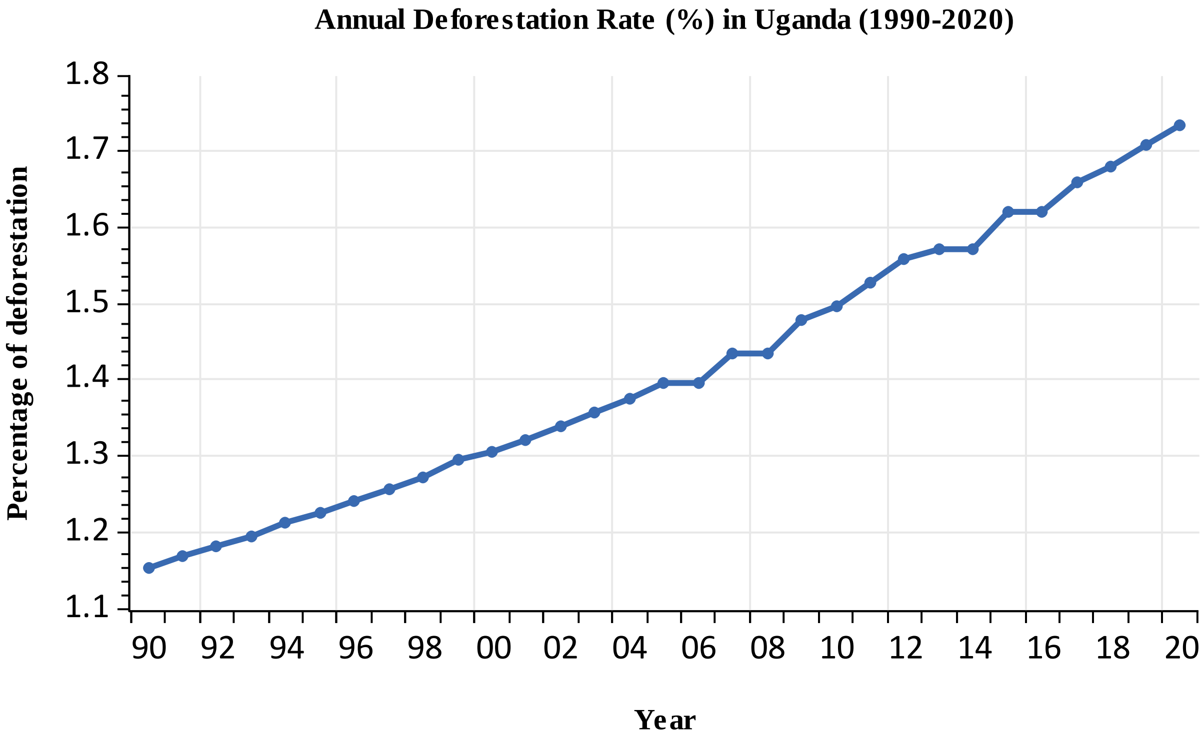
After a slight dip in 2012 to 3910.0 metric tons, emissions resumed their upward climb, reaching 4740.0 metric tons in 2014 and 4860.0 metric tons in 2015. The latter half of the decade saw even more pronounced increases, with emissions hitting 5670.0 metric tons in 2016 and peaking at 6130.0 metric tons in 2018. These record-high levels reflect the culmination of several factors, including sustained economic growth, significant increases in industrial activity, and extensive deforestation for agricultural expansion and urban development.

The trend of CO_2 emissions in Uganda from 1990 to 2020 thus illustrates the environmental impact of rapid economic growth, industrialization, and urbanization. The fluctuations and steady increases in emissions highlight the need for sustainable development practices and policies aimed at mitigating the adverse environmental effects of economic progress. These findings are consistent with patterns observed in other developing economies undergoing similar transitions, where economic growth often leads to increased CO_2 emissions unless countered by stringent environmental regulations and investments in green technologies.

4.1.2.2 Trend of Uganda's annual deforestation rate (%) for the period 1990 to 2020

Figure 4.2 traces the trend of deforestation rate (%) in Uganda from 1990 to 2020.

Figure 4. 2: Trend of Uganda's deforestation rate (%) 1990-2020.



Source: Author's analysis of World Bank data

The annual deforestation rate in Uganda from 1990 to 2020 shows a consistent upward trend, which closely parallels the rise in CO2 emissions over the same period. In 1990, the deforestation rate stood at 1.154040, reflecting the early stages of significant land-use changes. As Uganda began to experience economic growth and development, the pressure on forested areas increased, driven by the need for agricultural land, timber, and urban expansion. This led to a gradual increase in deforestation rates, reaching 1.211591 by 1994.

From the mid-1990s onwards, the deforestation rate accelerated, rising to 1.239573 in 1996 and 1.271400 by 1998. This period corresponds with the onset of more intensive agricultural practices and expanding urbanization, necessitating the clearing of forest land. The increase in manufacturing activities and infrastructure development also contributed to higher deforestation rates, as forests were cleared to make way for factories, roads, and residential areas. By 2000, the deforestation rate had climbed to 1.304152, a clear indication of the escalating demand for land resources.

The early 2000s saw continued growth in deforestation rates, reaching 1.339056 in 2002 and 1.358171 in 2003. This era was marked by increased economic activities and population growth, which further exacerbated the pressure on forest resources. As the economy diversified and industrial activities expanded, more land was required for both commercial and subsistence farming. By 2005, the deforestation rate had risen to 1.395232, mirroring the significant increase in CO2 emissions during this period.

The subsequent years witnessed even sharper increases in deforestation rates, with notable spikes in 2007 and 2009, where rates reached 1.433694 and 1.477722, respectively. These years were characterized by substantial economic growth, leading to higher energy demands and greater exploitation of natural resources. The deforestation rate peaked at 1.497497 in 2010, reflecting the cumulative impact of two decades of economic development and land-use changes.

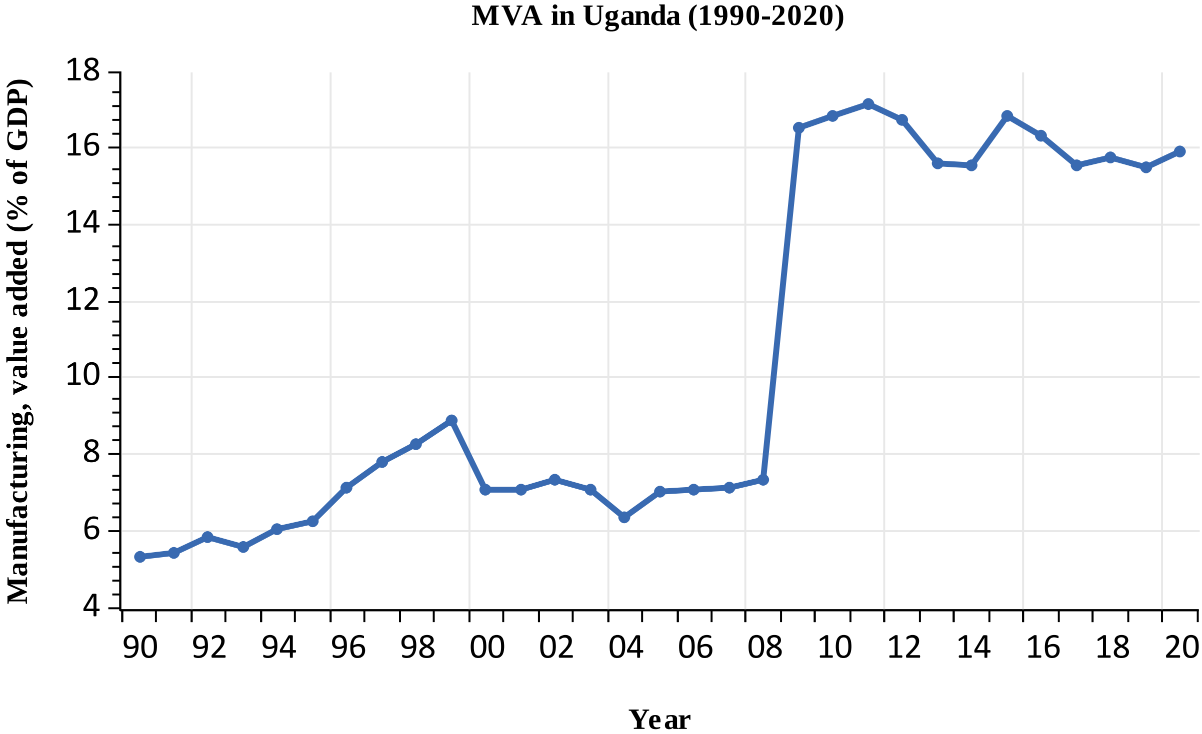
In the 2010s, the deforestation rate continued its upward trajectory, reaching 1.526810 in 2011 and 1.557268 in 2012. This period saw a sustained increase in CO2 emissions, correlating with the higher deforestation rates. The relationship between deforestation and CO2 emissions became increasingly evident as forest clearing for agriculture, urban development, and industrial activities released significant amounts of carbon stored in trees into the atmosphere. By 2015, the deforestation rate had climbed to 1.620621, further contributing to the rise in CO2 emissions.

The latter part of the decade showed continued increases in deforestation, with the rate reaching 1.658271 in 2017 and peaking at 1.709359 in 2019. This persistent rise underscores the ongoing challenges of balancing economic development with environmental sustainability. The high deforestation rates are primarily driven by the need for agricultural expansion, particularly in response to population growth and the increasing demand for food and fuelwood. Additionally, the expansion of urban areas and industrial zones continued to drive forest clearing.

Overall, the trend in annual deforestation rates from 1990 to 2020 highlights the significant environmental impact of Uganda's economic development. The steady increase in deforestation rates is closely linked to the rise in CO2 emissions, as forest loss directly contributes to higher carbon dioxide levels in the atmosphere. These trends underscore the urgent need for sustainable land management practices and policies aimed at reducing deforestation and mitigating its impact on CO2 emissions. Efforts to promote reforestation, improve agricultural practices, and implement stringent environmental regulations are essential to curbing these trends and achieving sustainable development in Uganda.

1.1.2.3 Trend of Uganda's manufacturing value added (1990-2020)

Figure 4. 3: Trend of Uganda's manufacturing value added (1990-2020)



Source: Author's analysis of World Bank data

The trend of Manufacturing Value Added (MVA) as a percentage of GDP in Uganda from 1990 to 2020 shows significant fluctuations, with an overall upward trajectory, particularly noticeable from the mid-1990s onwards. This trend closely relates to the rise in CO2 emissions over the same period, reflecting the industrial growth and its environmental impact.

In the early 1990s, MVA remained relatively stable, starting at 5.341026% in 1990 and slightly increasing to 5.820887% by 1992. This period was marked by modest industrial activities as Uganda's economy was still recovering from past political and economic instability. CO2 emissions during this time were low, aligning with the limited industrial output.

From 1993 to 1999, there was a marked increase in MVA, rising from 5.598406% to 8.893208%. This substantial growth can be attributed to economic reforms and liberalization policies implemented in the early 1990s, which attracted foreign investments and encouraged domestic industrial activities. The manufacturing sector expanded, leading to increased energy consumption and fossil fuel use, which in turn contributed to the rise in CO2 emissions. This period of industrial growth saw emissions rise from 820.0 metric tons in 1993 to 1320.0 metric tons in 1999.

However, the year 2000 marked a notable dip in MVA to 7.098978%, which remained relatively low until 2004, with slight variations. This decline could be attributed to economic challenges, including the impact of global market fluctuations and internal inefficiencies within the manufacturing sector. Despite this dip, CO2 emissions continued to rise, albeit at a slower pace, reflecting ongoing industrial activities and urban expansion.

The period from 2005 to 2008 saw a gradual recovery in MVA, increasing from 7.009316% to 7.306965%. This recovery coincided with renewed efforts to boost industrial output through policy support and infrastructure development. Consequently, CO2 emissions also saw a significant rise during this period, from 2230.0 metric tons in 2005 to 3180.0 metric tons in 2008, highlighting the direct correlation between manufacturing activities and emissions.

A significant surge in MVA occurred between 2009 and 2011, with values skyrocketing from 16.53152% in 2009 to 17.14687% in 2011. This sharp increase reflects substantial industrial expansion, possibly driven by large-scale investments in manufacturing and the implementation of industrial policies aimed at economic diversification. Correspondingly, CO2 emissions during this period rose dramatically from 3410.0 metric tons in 2009 to 4160.0 metric tons in 2011, underscoring the environmental impact of intensified manufacturing activities.

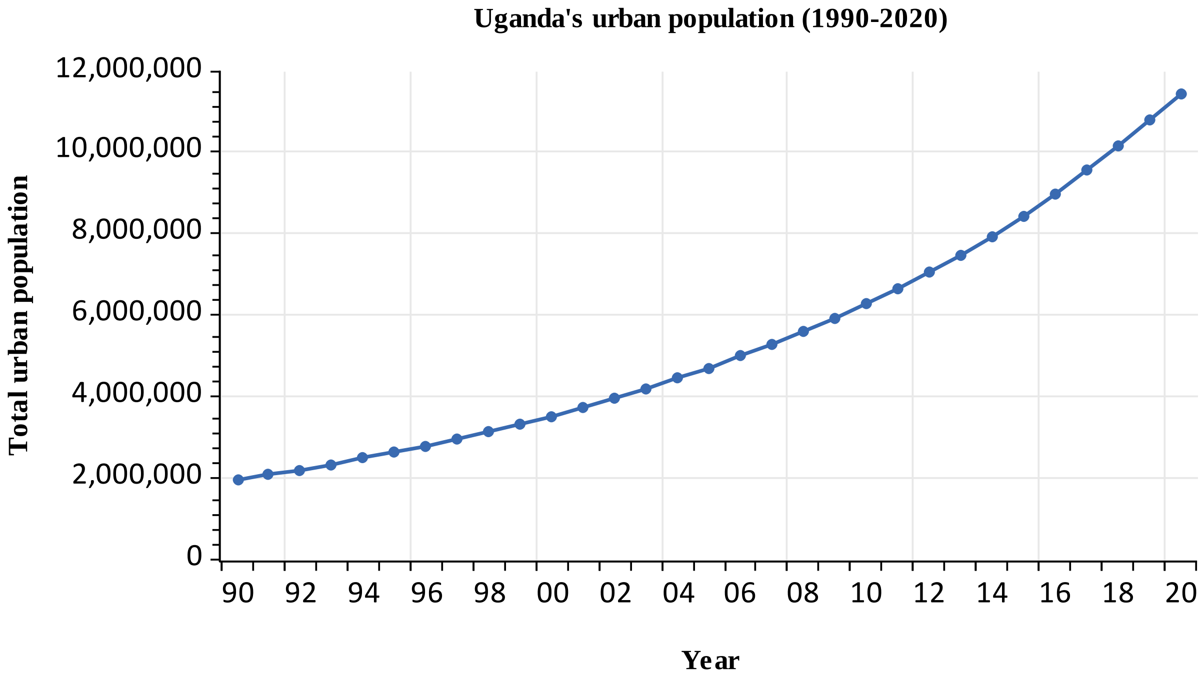
After peaking in 2011, MVA showed some variability, generally maintaining high levels but with slight declines, such as in 2013 and 2014 when it dropped to around 15.6%. These fluctuations indicate the manufacturing sector's responsiveness to economic conditions, including market demand and policy changes. Despite these variations, CO2 emissions continued to rise, reaching 4740.0 metric tons in 2014, reflecting sustained industrial activity and energy use.

In the latter part of the decade, MVA stabilized around 15-16%, with minor fluctuations, ending at 15.89301% in 2020. This stabilization indicates a mature phase of industrial development where the sector maintained its contribution to GDP despite broader economic challenges, including those posed by global economic conditions and internal structural issues. CO2 emissions mirrored this stabilization trend, peaking at 6130.0 metric tons in 2018 before slightly declining to 5943.0 metric tons in 2019, showing the persistent environmental impact of manufacturing activities.

Overall, the trend in MVA and CO2 emissions from 1990 to 2020 in Uganda highlights the direct link between industrial growth and environmental degradation. The significant increases in manufacturing activities, driven by economic reforms and investment, have substantially contributed to rising CO2 emissions, underscoring the need for sustainable industrial practices and policies to mitigate environmental impacts. This pattern is consistent with findings from other developing economies where industrial expansion often leads to increased emissions, necessitating balanced approaches to economic development and environmental conservation.

4.1.2.4 Trend of Uganda's total urban population (1990-2020)

Figure 4. 4: Trend of Uganda's total urban population (1990-2020)



Source: Author's analysis of World Bank data

The trend of urban population growth in Uganda from 1990 to 2020 shows a consistent and significant increase, which closely correlates with the rise in CO2 emissions over the same period. In 1990, Uganda's urban population was 1,922,173, reflecting a relatively small urban sector in a predominantly rural country. The urban population steadily increased each year, reaching 2,471,224 by 1994. This early growth phase can be attributed to internal migration as people moved from rural areas to cities in search of better employment opportunities and living conditions.

By the mid-1990s, the urban population continued to rise, reaching 2,969,697 in 1996 and 3,311,698 by 1998. This period was characterized by increased economic activities and urbanization driven by government policies aimed at boosting industrial growth and infrastructure development. As a result, cities expanded rapidly, and with this expansion came an increase in energy consumption, transportation, and industrial activities, all contributing to higher CO2 emissions. This urban growth mirrored the rise in CO2 emissions from 1,070.0 metric tons in 1996 to 1,320.0 metric tons in 1999.

The trend of urban population growth accelerated in the early 2000s, with the population reaching 4,697,306 by 2005. This significant increase is likely due to continued rural-to-urban migration, driven by better economic prospects in urban areas, and the natural population growth within cities. During this period, CO2 emissions also saw a substantial rise, increasing from 1,330.0 metric tons in 2000 to 2,230.0 metric tons in 2005. The correlation between urban population growth and CO2 emissions is evident, as expanding urban areas required more energy for housing, transportation, and industrial activities, leading to higher fossil fuel consumption and emissions.

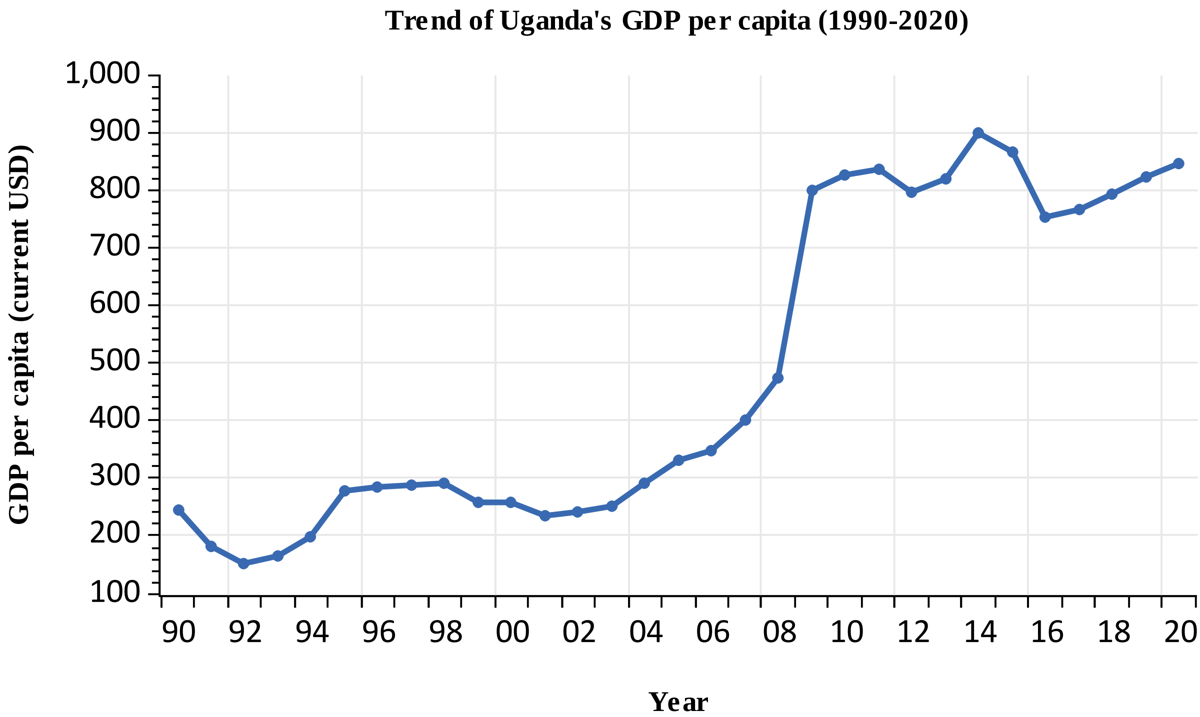
In the late 2000s and early 2010s, the urban population continued its upward trajectory, reaching 6,661,208 by 2011 and 7,480,857 by 2013. This growth was accompanied by significant infrastructural development and an increase in manufacturing and service industries in urban areas. The corresponding rise in CO2 emissions from 2,600.0 metric tons in 2006 to 4,270.0 metric tons in 2013 highlights the impact of urbanization on environmental degradation. Increased vehicle usage, higher electricity demand, and industrial emissions contributed to this trend.

The period from 2014 to 2020 saw an even more pronounced increase in the urban population, reaching 11,414,209 by 2020. This period was marked by intensified urban sprawl, the proliferation of informal settlements, and significant investments in urban infrastructure. The rise in CO_2 emissions during this time was equally significant, peaking at 6,130.0 metric tons in 2018. The rapid urban population growth exacerbated environmental pressures, as more land was converted for urban use, leading to deforestation and higher emissions from increased transportation and energy use.

Overall, the trend of urban population growth in Uganda from 1990 to 2020 is characterized by a consistent and substantial increase, driven by economic opportunities and internal migration. This growth has had a direct impact on CO_2 emissions, with urbanization contributing to higher energy consumption, transportation needs, and industrial activities, all of which increase fossil fuel use and emissions. The findings align with trends observed in other developing countries, where rapid urbanization often leads to environmental challenges. Addressing these issues requires integrated urban planning, investments in sustainable infrastructure, and policies aimed at reducing the carbon footprint of growing urban areas.

4.1.2.5 Trend of Uganda's Gross Domestic Product per capita (1990-2020)

Figure 4.5: Trend of GDP per capita in Uganda from 1990 to 2020



The trend of GDP per capita in Uganda from 1990 to 2020 depicted in figure 4.5 shows significant fluctuations, which closely correlate with the trends in CO_2 emissions over the same period. In 1990, Uganda's GDP per capita was relatively low at 244.7541 USD, reflecting the country's recovery phase from past economic and political turmoil. However, there was a notable decline in the early 1990s, reaching a low of 151.9765 USD in 1992. This decline can be attributed to economic instability, poor infrastructure, and low industrial output, resulting in relatively stable but low CO2 emissions around this time, approximately 820 metric tons.

From the mid-1990s onwards, there was a gradual improvement in GDP per capita, rising to 278.3166 USD in 1995 and 284.4568 USD in 1996. This period of economic recovery and growth was driven by economic reforms, liberalization policies, and increased foreign investment. The manufacturing and services sectors began to expand, leading to a rise in CO2 emissions from 960 metric tons in 1995 to 1070 metric tons in 1996. This increase in emissions reflects the growth in industrial activities and energy consumption associated with economic development.

In the late 1990s, GDP per capita continued to show a modest increase, peaking at 292.1695 USD in 1998 before experiencing a slight dip to 257.6786 USD in 1999. This period saw fluctuating economic performance due to external economic shocks and domestic challenges. Despite these fluctuations, CO2 emissions continued to rise, reaching 1320 metric tons in 1999. The ongoing industrialization and urbanization contributed to this trend, even though GDP per capita did not show consistent growth.

The early 2000s witnessed further fluctuations in GDP per capita, with values ranging from 257.8296 USD in 2000 to 241.8689 USD in 2002, reflecting economic instability and policy adjustments. However, from 2003 onwards, there was a more consistent upward trend in GDP per capita, reaching 292.4727 USD in 2004 and 330.6029 USD in 2005. This growth period was marked by increased economic stability, infrastructural development, and investment in key sectors. Correspondingly, CO2 emissions saw a significant increase, rising from 1350 metric tons in 2001 to 2230 metric tons in 2005, indicating the environmental impact of economic expansion.

The late 2000s to early 2010s showed substantial growth in GDP per capita, peaking at 799.9296 USD in 2009 and 824.7377 USD in 2010. This period was characterized by strong economic performance, driven by industrial growth, increased exports, and infrastructural improvements. The CO2 emissions during this time also surged dramatically, from 3180 metric tons in 2008 to 3850 metric tons in 2010, highlighting the environmental costs of rapid economic growth.

Following a peak in GDP per capita in 2011 at 837.0959 USD, there was a slight decline to 796.7111 USD in 2012, followed by a recovery to 819.7579 USD in 2013 and further growth to 897.5097 USD in 2014. This period saw continued industrialization and urbanization, contributing to rising CO2 emissions, which reached 4740 metric tons in 2014. The correlation between economic growth and emissions is evident, as increased industrial and economic activities drive higher energy consumption and fossil fuel use.

The mid to late 2010s witnessed some variability in GDP per capita, with a notable decline in 2016 to 753.6844 USD due to economic challenges but a subsequent recovery to 846.7672 USD by 2020. CO2 emissions mirrored these trends, with a peak at 6130 metric tons in 2018 before slightly declining to 5943 metric tons in 2019. This period reflects the balance between economic development and the environmental impacts of increased industrial and urban activities.

Overall, the trend in GDP per capita in Uganda from 1990 to 2020 shows a clear connection with CO2 emissions, illustrating the environmental consequences of economic growth. As GDP per capita increased, driven by industrialization, urbanization, and infrastructural development, CO2 emissions also rose significantly. This trend underscores the need for sustainable development practices that balance economic growth with environmental conservation to mitigate the adverse impacts of industrial activities on the environment.

4.2 Bivariate Analysis

4.2.1 Correlation analysis

In order to confirm whether the sample was reliable, correlation analysis was conducted to test the null hypothesis that the correlation between each variable and the dependent variable was Zero. The findings are presented in Table 4.2

Table 4. 2: Correlation Matrix of Uganda's Inflation, broad money, Lending interest rate, Real Effective Exchange Rate and Final Consumption Expenditure

	LNCO2E	LNADR	LNMVA	LNUP	LNGDPC
LNCO2E	1.000000	0.984860	0.899132	0.987072	0.953005
LNADR	0.984860	1.000000	0.895867	0.998719	0.932281
LNMVA	0.899132	0.895867	1.000000	0.884769	0.959131
LNUP	0.987072	0.998719	0.884769	1.000000	0.927928
LNGDPC	0.953005	0.932281	0.959131	0.927928	1.000000

Source: Author's analysis of World Bank data

The correlation matrix in Table 4.2 The correlation matrix provides insights into the relationships between the natural logarithms of CO2 emissions (LNCO2E), annual deforestation rate (LNADR), manufacturing value added (LNMVA), urban population (LNUP), and GDP per capita (LNGDPC) in Uganda. Here is a detailed explanation of the results:

LNCO2E (CO2 Emissions) and Other Variables:

LNADR (Annual Deforestation Rate): The correlation coefficient between LNCO2E and LNADR is 0.984860, indicating a very strong positive relationship. This suggests that higher deforestation rates are closely associated with increased CO2 emissions. Deforestation contributes to CO2 emissions as trees, which act as carbon sinks, are removed, releasing stored carbon into the atmosphere.

LNMVA (Manufacturing Value Added): The correlation between LNCO2E and LNMVA is 0.899132, which indicates a strong positive relationship. This suggests that as the manufacturing sector grows, CO2 emissions also increase. Manufacturing activities typically involve energy consumption and industrial processes that produce CO2 emissions.

LNUP (Urban Population): The correlation coefficient between LNCO2E and LNUP is 0.987072, indicating a very strong positive relationship. As the urban population increases, CO2 emissions rise significantly, likely due to increased energy consumption, transportation, and industrial activities associated with urbanization.

LNGDPC (GDP per Capita): The correlation between LNCO2E and LNGDPC is 0.953005, indicating a strong positive relationship. Economic growth, as measured by GDP per capita, tends to be accompanied by higher CO2 emissions due to greater industrial activities, energy use, and transportation.

1. **LNADR (Annual Deforestation Rate) and Other Variables:**

LNMVA (Manufacturing Value Added): The correlation between LNADR and LNMVA is 0.895867, indicating a strong positive relationship. This relationship suggests that increased manufacturing activities lead to higher deforestation rates, possibly due to land clearance for industrial purposes.

LNUP (Urban Population): The correlation coefficient between LNADR and LNUP is 0.998719, which shows an almost perfect positive correlation. This extremely high correlation implies that urban population growth is closely associated with increased deforestation. Urban expansion often results in the conversion of forested areas to urban land uses.

LNGDPC (GDP per Capita): The correlation between LNADR and LNGDPC is 0.932281, indicating a strong positive relationship. Economic growth is associated with higher deforestation rates, likely due to increased demand for land and natural resources.

2. **LNMVA (Manufacturing Value Added) and Other Variables:**

LNUP (Urban Population): The correlation coefficient between LNMVA and LNUP is 0.884769, indicating a strong positive relationship. This suggests that manufacturing growth is associated with urban population increases, as industrial activities attract people to urban areas for job opportunities.

LNGDPC (GDP per Capita): The correlation between LNMVA and LNGDPC is 0.959131, indicating a very strong positive relationship. This suggests that as manufacturing value added increases, GDP per capita also rises, reflecting the importance of the manufacturing sector in driving economic growth.

3. **LNUP (Urban Population) and LNGDPC (GDP per Capita):**

The correlation coefficient between LNUP and LNGDPC is 0.927928, indicating a strong positive relationship. This suggests that as the urban population grows, GDP per capita increases. Urbanization is often associated with improved economic activities, better infrastructure, and greater access to services, which contribute to economic growth.

4.3 Diagnostic tests

4.3.1 Test for normality

Table 4.3 shows a summary of the results of the Jarque-Bera normality test.

Table 4. 3: Results of the Test for Normality Before Taking First Difference

	CO2E	ADR	MVA	UP	GDPC
Jarque-Bera	3.197411	2.049052	4.645877	2.803958	4.353215
Probability	0.202158	0.358966	0.097985	0.246109	0.113426
Observations	31	31	31	31	31

Source: Author's Analysis of World Bank data 1994-2020

The Jarque-Bera test results presented in Table 4.3 assess the normality of the distributions for CO2 emissions (CO2E), annual deforestation rate (ADR), manufacturing value added (MVA), urban population (UP), and GDP per capita (GDPC) before taking the first difference. The test statistics for CO2E, ADR, MVA, UP, and GDPC are 3.197411, 2.049052, 4.645877, 2.803958, and 4.353215, respectively. The corresponding p-values are 0.202158 for CO2E, 0.358966 for ADR, 0.097985 for MVA, 0.246109 for UP, and 0.113426 for GDPC. Given that all p-values are greater than the conventional significance levels (0.01, 0.05, and 0.10), we fail to reject the null hypothesis of normality for each of the variables. This indicates that the data for CO2 emissions, annual deforestation rate, manufacturing value added, urban population, and GDP per capita are approximately normally distributed. Such normality in the distribution is crucial for the validity of many statistical analyses and econometric models, including those employed in this study. These findings suggest that the assumptions of normality hold for the variables in their levels, thus providing a solid foundation for subsequent econometric modelling and analysis.

4.3.2 Test for Multicollinearity

Table 4. 4: Variance Inflation Factor for the series

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
ADR	0.008852	121.39503	3.291351
MVA	790383.1	523.6334	7.754422
UP	0.006375	127.5389	3.211892
GDPc	1.60E-20	7.741347	2.186159
C	413.3180	551.5664	NA

Source: Author's analysis of World Bank data

The test for multicollinearity, as shown in Table 4.4, used the Variance Inflation Factor (VIF) to evaluate the correlation among the independent variables in the regression model. The centered VIF values for the Annual Deforestation Rate (ADR), Manufacturing Value Added (MVA), Urban Population (UP), and GDP per capita (GDPc) were 3.29, 7.75, 3.21, and 2.19, respectively, all of which fell below the commonly accepted threshold of 10. These results suggest that multicollinearity is not a significant issue within the model, indicating that the independent variables are not highly correlated to the extent that would distort the regression coefficients or inflate their standard errors. Conversely, the uncentered VIF values are substantially higher, particularly for ADR and UP, with values of 121.40 and 127.54, respectively. This discrepancy is likely due to the inclusion of the constant term, which can artificially inflate VIF values when strong linear relationships exist between the independent variables and the intercept. Despite these elevated uncentered VIFs, the more relevant centered VIFs confirm that multicollinearity is within acceptable limits, thereby ensuring the reliability and interpretability of the regression model's results.

4.3.3 Test Stationarity

To avoid getting spurious results, it was necessary to determine the order of integration of the series prior to running the regression. With intercept, no trend, and adopting the null hypothesis as $H_0 : \beta_i = 0$ against the alternative that the data was stationary ($H_1 : \beta_i < 1$), and critical value of 5%, the series were tested for stationarity using the Augmented Dickey-Fuller (ADF) test with results as presented in Table 4.5.

Table 4. 5: Summary of ADF Unit Root Test Statistics for the Individual series

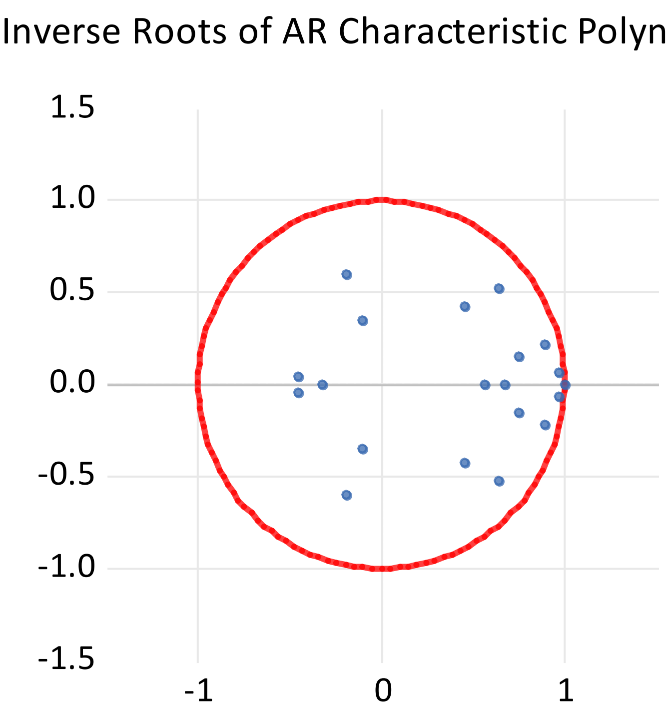
Series	**Lag**	***I* (0) ADF t & prob**	**Critical**	***I (1)* ADF-**	**Critical values**	**Order**
LNCO2E	2	-1.051183 (0.7332)	-2.885249	-3.838673(0.0034)	-2.885249	I (1)
LNADR	2	0.884511 (0.5911)	-2.885450	-7.869466 (0.0000)	-2.885654	I (1)
LNMVA	2	-1.377785 (0.0613)	-2.885249	-4.505707 (0.0003)	-2.885249	I (1)
LNUP	2	-0.199406 (0.9343)	-2.885450	-3.468208 (0.0105)	-2.885654	1 (1)
LNGDPc	2	-1.330495 (0.6138)	-2.885249	-3.555037 (0.0081)	-2.885249	I (1)

Source: Author's analysis of World Bank

The results of the Augmented Dickey-Fuller (ADF) test for stationarity, presented in Table 4.5, reveal the integration order of the series under study: CO2 emissions (LNCO2E), annual deforestation rate (LNADR), manufacturing value added (LNMVA), urban population (LNUP), and GDP per capita (LNGDPc). For all variables, the null hypothesis of non-stationarity (H_0: β_i=0) could not be rejected at levels (I(0)) since their ADF test statistics and associated p-values were greater than the critical values at the 5% significance level. Specifically, LNCO2E, LNADR, LNMVA, LNUP, and LNGDPc had ADF statistics of -1.051183 (p = 0.7332), 0.884511 (p = 0.5911), -1.377785 (p = 0.0613), -0.199406 (p = 0.9343), and -1.330495 (p = 0.6138), respectively, all failing to surpass the critical threshold of -2.885249. However, after first differencing (I(1)), the series became stationary, as indicated by the significant ADF test statistics and p-values well below the 5% critical value. The first-differenced ADF statistics were -3.838673 (p = 0.0034) for LNCO2E, -7.869466 (p = 0.0000) for LNADR, -4.505707 (p = 0.0003) for LNMVA, -3.468208 (p = 0.0105) for LNUP, and -3.555037 (p = 0.0081) for LNGDPc, all exceeding their respective critical values. This indicates that each series is integrated of order one (I(1)), confirming their stationarity after first differencing and validating the suitability for further regression analysis to avoid spurious results.

4.3.4 Test for Model Stability

Figure 4. 5: Inverse Roots of AR Characteristic Polynomial Indicating Model Stability



Source: Author's analysis of World Bank data

Figure 4.5 shows the AR roots graph of the vector error correction model (VECM) for the determinants of CO2 emissions in Uganda from 1990 to 2020 which visually represents the inverse roots of the characteristic polynomial. For the model to be considered stable, all the roots must lie within the unit circle, which is represented by the boundary of the red circle in the graph. The graph displays several points, each representing an inverse root, and all of them fall inside the unit circle. This indicates that the VECM is stable and appropriately specified. The stability of the VECM implies that the long-run equilibrium relationships among the variables—CO2 emissions, annual deforestation rate, manufacturing value added, urban population, and GDP per capita—are robust, and the system will return to equilibrium following a shock. These results are critical for ensuring the reliability of the VECM in providing accurate and meaningful insights into the dynamics and determinants of CO2 emissions in Uganda over the study period.

4.4 Estimation of the Econometric Model

4.4.1 Optimal Lag Length Selection

Before proceeding to conduct the Johansen cointegration test, it was imperative to identify the most appropriate lag length for the cointegration analysis. To achieve this, various lag selection criteria were employed, including the Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC), and Hannan–Quinn Criterion (HQC). Utilizing EViews 13, an unrestricted Vector Autoregression (VAR) model was estimated with potential lag intervals for the endogenous variables ranging from 1 to 4 lags. The optimal lag length was determined by analysing the VAR order lag selection table. The criterion with the lowest value, indicated by an asterisk, and the lag corresponding to the highest number of asterisks, was selected. Consequently, the AIC criterion was chosen, resulting in a lag length of 2.

Table 4. 6: VAR Lag Order selection criteria (Endogenous variables: LNCO2E, LNADR, LNMVA, LNUP, LNGDPc and Exogenous variables: C)

Lag	LogL	LR	FPE	AIC	SC	HQ
0	620.5151	NA	2.41e-11	-10.25858	-10.14244	-10.21142
1	2193.628	2988.915	1.50e-22	-36.06047	-35.36359	-35.77746
2	2410.273	393.5717*	6.18e-24*	-39.25455*	-37.97695*	-38.73571*
3	2418.403	14.09211	8.23e-24	-38.97338	-37.11506	-38.21871
4	2439.695	35.13137	8.84e-24	-38.91158	-36.47253	-37.92107

* Indicates lag order selected by the criterion. **LR**: sequential modified LR test statistic (each test at 5% level), **FPE:** Final prediction error, **AIC:** Akaike information criterion, **SC:** Schwarz information criterion, **HQ:** Hannan-Quinn information criterion.
Source: Author's analysis of World Bank data

4.4.2 The Johansen Cointegration Test

Table 4. 7: Unrestricted Cointegration Rank Test (Trace and Maxi-Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.** Critical Value	Max-Eigen Statistic	0.05 Critical Value	Prob.** Critical Value
None *	0.294895	89.65475	69.81889	0.0006	42.27838	33.87687	0.0040
At most 1	0.187376	47.37637	47.85613	0.0554	25.10583	27.58434	0.1005
At most 2	0.122639	22.27054	29.79707	0.2837	15.83127	21.13162	0.2349
At most 3	0.045971	6.439267	15.49471	0.6436	5.694390	14.26460	0.6527
At most 4	0.006137	0.744877	3.841465	0.3881	0.744877	3.841465	0.3881

Trace test indicates 1 cointegrating equation(s) at the 0.05 level. Max-eigenvalue test indicates 1 cointegrating equation(s) at the 0.05 level. * denotes rejection of the hypothesis at the 0.05 level **MacKinnon-Haug-Michelis (1999) p-values.
Source: Author analysis of World Bank Data

The results of the Johansen Cointegration Test, as presented in Table 4.7, reveal critical insights into the long-run relationships among the variables under study. The test employs both Trace and Max-Eigenvalue statistics to assess the number of cointegrating equations. According to the Trace test, there is evidence of one cointegrating equation at the 5% significance level, as indicated by the Trace statistic of 89.65475, which exceeds the critical value of 69.81889 with a p-value of 0.0006. Similarly, the Max-Eigenvalue test confirms the presence of one cointegrating equation, with a Max-Eigen statistic of 42.27838 surpassing the critical value of 33.87687 and a p-value of 0.0040. These findings denote the rejection of the null hypothesis of no cointegration for the "None" hypothesis, suggesting a stable long-term equilibrium relationship among the variables. However, for higher hypothesized numbers of cointegrating equations (At most 1, At most 2, At most 3, and At most 4), the test statistics do not exceed the corresponding critical values, indicating no additional cointegrating relationships at these levels. Thus, the Johansen Cointegration Test robustly supports the existence of one significant cointegrating vector, affirming the long-term interdependencies between CO2 emissions, annual deforestation rate, manufacturing value added, urban population, and GDP per capita in Uganda from 1990 to 2020.

4.4.3 The Normalized Coefficients

Table 4. 8: Normalized Cointegrating Equation

1 Cointegrating Equation

Log-Likelihood: 2415.665

Normalized cointegrating coefficients (standard error in parentheses)

LNCO2E	LNADR	LNMVA	LNUP	LNGDPC	C
1.000000	19.30448	0.333125	-5.219857	-0.828100	70.21106
	(3.28493)	(0.13329)	(0.73370)	(0.10847)	
	[5.87669]	[2.49933]	[-7.11444]	[-7.63418]	

** Denotes significance at 5%

Source: Author analysis of World Bank Data

The cointegrating equation describes the long-term relationship among the variables, indicating how deviations from this equilibrium are corrected over time. The cointegrating equation can be expressed as:

$$LNCO2E=-19.30448 \cdot LNADR+0.333125 \cdot LNMVA-5.219857 \cdot LNUP-0.828100 \cdot LNGDPC+70.21106$$

4.4.3.1 The effect of the annual deforestation rate (LNADR) on CO2 emissions in Uganda

The coefficient for LNADR (19.30448), with a standard error of 3.28493 and a t-statistic of 5.87669, is expected and suggests a significant positive relationship between LNADR and LNCO2E, significant at the 5% level. This indicates that a 1% increase in the annual deforestation rate (LNADR) is associated with a 19.30% increase in CO2 emissions in the long term, highlighting the substantial impact of deforestation on CO2 emissions. The statistical significance of this relationship is confirmed by a t-statistic of 5.87669, indicating a strong correlation.

4.4.3.2 The effect of Manufacturing Value Added on CO2 emissions in Uganda

In contrast, the coefficient for Manufacturing Value Added (MVA) is 0.333125, with a standard error of 0.133125 and a t-statistic of 2.49933. This indicates that a 1% increase in manufacturing value added corresponds to a 0.33% increase in CO2 emissions. The positive relationship between MVA and CO2 emissions is statistically significant, as evidenced by the t-statistic exceeding the critical value at the 5% significance level.

4.4.3.3 The effect of Urban Population (LNUP) on CO2 emissions in Uganda

The coefficient for LNUP is -5.219857, with a standard error of 0.73370 and a t-statistic of -7.63418. This significant negative relationship (at the 5% level) indicates that a 1% increase in urban population is associated with a 5.22% decrease in CO2 emissions. This result suggests that urban population growth, perhaps due to increased efficiency or environmental policies in urban areas, is inversely related to CO2 emissions

4.4.3.4 The effect of Gross Domestic Product per capita (LNGDPc) on CO2 emissions in Uganda

The coefficient for LNGDPc is -0.828100, with a standard error of 0.10847 and a t-statistic of -7.11444. This coefficient is statistically significant at the 5% level, implying that a 1% increase in GDP per capita corresponds to a 0.83% decrease in CO2 emissions. This finding suggests that higher GDP per capita is associated with lower CO2 emissions, potentially reflecting the adoption of cleaner technologies or more efficient production processes as income levels rise.

4.4.4 The estimated short run (Error Correction) Model

Table 4.8 below presents the results from the estimated short run (Error Correction) Model. This table highlights the short-term dynamics between the dependent and independent variables, indicating how quickly deviations from the long-term equilibrium are corrected. The results provide insights into the immediate effects of changes in broad money supply, lending interest rates, real effective exchange rate, and final consumption expenditure on inflation in Uganda.

Table 4. 9: Error correction estimates (Appendix 1.)

The short-run (error correction) model estimates presented in Appendix 1 depict the short-term dynamics and adjustments ofCO2 emissions (LNCO2E) the annual deforestation rate (LNADR), manufacturing value added (LNMVA), Urban population (LNUP), and GDP per capita (LNGDPc) in Uganda, in response to deviations from long-term equilibrium. The error correction term (COINTEQ1) reflects the speed at which the variables return to equilibrium after a shock.

4.4.4.1 The error correction term (COINTEQ1)

The error correction term (COINTEQ1) shows that deviations from the long-term equilibrium are corrected over time. Specifically, the coefficient for the CO2 emissions equation (-0.056730) suggests that 5.67% of any disequilibrium in the previous period's CO2 emissions is corrected in the current period. This negative and significant value (t-stat = -2.91632) indicates a moderate speed of adjustment towards the long-run equilibrium. Similarly, the negative coefficients in the equations for annual deforestation rate (-0.004461, t-stat = -2.17016), manufacturing value added (-0.103869. t-stat=-2.54372) imply correction speeds of 0.45% and 10.4% per period, respectively. The coefficients for urban population and GDP per capita are not statistically significant, suggesting that these variables do not exhibit a significant short-term adjustment towards long-term equilibrium.

4.4.4.2 The short run effect of annual deforestation rate on CO2 emissions in Uganda

For the annual deforestation rate (D(LNADR)), the first lag (D(LNADR(-1))) shows a positive effect of approximately 35.68%, though this result is not statistically significant, suggesting that recent increases in deforestation might have a moderate but uncertain impact on CO2 emissions. The second lag (D(LNADR(-2))) also displays a positive effect of around 57.30%, but again, this is not statistically significant. However, the third lag (D(LNADR(-3))) reveals a significantly higher positive impact of about 119.70% on CO2 emissions, indicating that deforestation from three years prior has a substantial and statistically significant effect, reflecting the cumulative and escalating nature of deforestation's impact over time.

4.4.4.3 The short run effect of Manufacturing value added on CO2 emissions in Uganda

Regarding Manufacturing Value Added (D(LNMVA)), the first lag (D(LNMVA(-1))) shows a modest and statistically insignificant effect of approximately -2.86%, suggesting that recent changes in manufacturing value added might have a slight and uncertain impact on CO2 emissions. The second lag (D(LNMVA(-2))) presents a minimal and statistically insignificant effect of about 0.32%, indicating negligible immediate impact. The third lag (D(LNMVA(-3))) also shows a minor and statistically insignificant effect of about 0.53%, further reinforcing the limited short-term influence of manufacturing value added on CO2 emissions.

4.4.4.4 The effect of Urban population on CO2 emissions in Uganda

For the urban population (D(LNUP)), the first lag (D(LNUP(-1))) exhibits a significant positive effect of approximately 208.37%, meaning that an increase in urban population from the previous quarter has a considerable impact on CO2 emissions. The second lag (D(LNUP(-2))) displays a positive but statistically insignificant effect of about 98.62%, indicating that the impact of urban population growth might persist over time but with uncertain magnitude. The third lag (D(LNUP(-3))) shows a significant positive effect of approximately 251.90%, emphasizing the strong influence of urban population growth over a longer period on CO2 emissions.

4.4.4.5 The effect of GDP per capita on CO2 emissions in Uganda.

Finally, for GDP per capita (D(LNGDPC)), the first lag (D(LNGDPC(-1))) demonstrates a statistically significant positive effect of about 1.75%, suggesting that recent increases in GDP per capita lead to a slight rise in CO2 emissions. The second lag (D(LNGDPC(-2))) has a minimal and statistically insignificant effect of about -3.23%, indicating a potential but uncertain decrease in emissions. The third lag (D(LNGDPC(-3))) shows a small and statistically insignificant positive effect of approximately -3.10%, further reflecting the limited impact of GDP per capita on CO2 emissions in the short run.

4.4.4.5 Intercept of the Short run model

The intercept term of the short-run error correction model provides insights into the baseline effects on CO2 emissions when all its determinants studied in the current study are held constant. The intercept for CO2 emissions is -0.0834, though it is statistically insignificant at conventional levels, indicating that the baseline effect on CO2 emissions is not robustly supported by the data. This result suggests that the changes in CO2 emissions are more significantly influenced by the included variables and their lags rather than by a constant baseline effect. Conversely, this non-significance implies that other factors or variables might be more influential in determining CO2 emissions, rather than a constant baseline effect.

4.4.4.6 Short run model diagnostics

The model diagnostics reveal several important aspects of the model's performance. The R-squared values range from 0.506 for the annual deforestation rate to 0.727 for GDP per capita, indicating a moderate to strong fit of the model to the data, with the highest value observed for GDP per capita. The adjusted R-squared values are slightly lower, ranging from 0.429 for the annual deforestation rate to 0.684 for GDP per capita, but still reflect a reasonable fit, particularly for the CO2 emissions equation, which has an adjusted R-squared of 0.588. The sum of squared residuals is low across the models, with values of 0.0184 for CO2 emissions, 0.0002 for annual deforestation rate, 0.0812 for manufacturing value added, 0.00001 for urban population, and 0.0396 for GDP per capita, suggesting that the model fits the data well. The standard errors of the equations range from 0.0014 for the annual deforestation rate to 0.0281 for manufacturing value added, indicating precise estimates. The F-statistics are significant for most models, with values of 11.621 for CO2 emissions, 6.593 for annual deforestation rate, 9.456 for manufacturing value added, 11.121 for urban population, and 17.104 for GDP per capita, highlighting that the models overall are statistically significant and provide a good explanation of the variability in the dependent variables. These diagnostics suggest that the models are robust and adequately capture the relationships between the variables and CO2 emissions, despite some individual variable coefficients and intercepts being statistically insignificant.

4.4.5 Residual diagnostic Tests

Table 4. 10: Summary of results from residual diagnostic tests for serial correlation, normality and heteroskedasticy

RESIDUAL TEST	STATISTIC	LAG	VALUE	DF	PROBABILITY
VEC LM. Serial correlation	LRE*stat	2	34.36092	25	0.1209
	Rao-F-stat	2	1.531397	(25, 34.9)	0.1209
	LRE*stat	3	36.07600	25	0.0871
	Rao-F-stat	3	1.641595	(25.34.9)	0.0871
Normality	Jarque-Bera		2.685890	**2**	0.2611
			1.177026	2	0.5552
			2.277924	2	0.1312
			4.097551	2	0.1289
			2.752949	2	0.2525
Heteroskedasticity	Joint Chi-sq		510.9139	480	0.1590

Source: Author's analysis of World Bank data

The results from the residual diagnostic tests in Table 4.10 indicate that the vector error correction (VEC) model demonstrates robust properties essential for valid inference. These tests included evaluations for serial correlation, normality, and heteroskedasticity in the residuals.

4.4.5.1 Serial Correlation

The results from the serial correlation tests indicate that the vector error correction (VEC) model did not exhibit significant evidence of serial correlation in the residuals, given that the corresponding probability values were above the conventional significance level of 0.05 suggesting that the null hypothesis (which states that there is no serial correlation) could not be rejected. Specifically, the LRE stat for lag 2 yielded a probability value of 0.1209, and the Rao-F statistic for lag 2 also showed a probability of 0.1209. For lag 3, the LRE stat. produced a probability value of 0.0871, while the Rao-F statistic for lag 3 reported a probability of 0.0871. These results suggested that the null hypothesis of no serial correlation could not be rejected, supporting the assumption that the residuals were likely serially uncorrelated.

4.4.5.2 Normality

The Jarque-Bera test was used to assess whether the residuals followed a normal distribution. Multiple Jarque-Bera statistics were reported, each with different values and associated degrees of freedom, but all probabilities exceeded the 0.05 threshold. Specifically, the probabilities for components 1, 2, 3, 4 and 5 of the tests were 0.2611, 0.5552, 0.1312, 0.1289, and 0.2525, all exceeding the conventional significance level of 0.05. Consequently, these findings indicated that the null hypothesis of normality could not be rejected, suggesting that the residuals were approximately normally distributed, an important condition for the validity of the model's inferences.

4.4.5.3 Heteroskedasticity

The White heteroskedasticity test (excluding cross terms) was used to assess if the variance of the residuals remained consistent across observations. As shown in Table 4.10, the joint Chi-squared test for heteroskedasticity revealed a test statistic of 510.9139 with a probability of 0.1590. This probability value suggested that the null hypothesis of homoskedasticity, or constant variance of the residuals, could not be rejected. As a result, the analysis indicated that the residuals did not exhibit significant heteroskedasticity, which is favourable for the assumptions underlying the model and enhances the reliability of the results obtained from the analysis.

The above results from residual diagnostic tests show that the Vector Error Correction Model (VECM) was an effective tool for analysing the long-term and short-term dynamics of CO2 emissions and their determinants in Uganda. Consequently, the findings derived from this model are credible and provide a solid foundation for understanding the relationships and impacts of the studied variables.

4.5 Discussion of Results

4.5.1 Discussion of results on the effect of ADR on CO2 emissions in Uganda

The results indicating a significant positive relationship between the annual deforestation rate (LNADR) and CO2 emissions (LNCO2E) in Uganda, with a coefficient of 19.30448 and a t-statistic of 5.87669, align well with the findings in the broader empirical literature. This coefficient suggests that a 1% increase in the annual deforestation rate is associated with a substantial 19.30% increase in CO2 emissions in the long term, highlighting the severe impact of deforestation on environmental sustainability. The coefficient of 19.30448, with a t-statistic of 5.87669, suggests that deforestation considerably elevates CO2 emissions, which is consistent with the global understanding that forests act as crucial carbon sinks. The extensive deforestation in Uganda, as evidenced by the studies, directly diminishes the country's ability to sequester carbon, thereby exacerbating CO2 emissions. This relationship is supported by the significant positive elasticity indicating that a 1% increase in deforestation correlates with a 19.30% increase in CO2 emissions in the long run, highlighting the critical need for effective forest management policies. The statistical significance of this relationship, confirmed by the t-statistic, underscores the robust nature of this correlation and the critical importance of addressing deforestation to mitigate CO2 emissions.

Empirical studies from various regions corroborate these findings. For instance, Kocoglu et al. (2024) demonstrated the potential of forests to mitigate CO2 emissions globally, emphasizing the importance of forest conservation in environmental strategies. Similarly, Raihan et al. (2022a) and Begum et al. (2020) found significant adverse impacts of deforestation on CO2 emissions in Malaysia, highlighting the need for sustainable land management practices. In East Asia, Mighri et al. (2022) showed that strategic forest investments could effectively reduce CO2 emissions, a notion supported by Selvanathan et al. (2023) in the context of OECD countries, despite some mixed findings. Additionally, studies by Sakala et al. (2023) in SSA and local research by Naturinda et al. (2019) and Olupot et al. (2017) in Uganda emphasize the significant carbon sequestration role of forests and the detrimental effects of deforestation on CO2 emissions. These studies collectively underline the necessity for comprehensive forest conservation policies to address the substantial impact of deforestation on CO2 emissions and support long-term environmental sustainability.

4.5.2 Discussion of results on the effect of MVA on CO2 emissions in Uganda

The empirical analysis demonstrates a statistically significant positive relationship between Manufacturing Value Added (MVA) and CO2 emissions in Uganda, as evidenced by a coefficient of 0.333125, with a standard error of 0.133125 and a t-statistic of 2.49933. This implies that a 1% increase in MVA corresponds to a 0.33% increase in CO2 emissions, highlighting the environmental impact of industrial growth. The significance of the t-statistic at the 5% level underscores the robustness of this relationship, suggesting that manufacturing activities significantly contribute to the increase in CO2 emissions.

This observed relationship is consistent with findings from broader empirical literature on the effects of industrialization on CO2 emissions. In OECD countries, despite advancements in technology and stringent environmental regulations, industrial activities remain a primary source of CO2 emissions, as highlighted by Wang et al. (2021). The ASEAN region, experiencing rapid industrialization, faces significant environmental challenges due to reliance on fossil fuels and lack of stringent emission control policies, as noted by Zafar et al. (2020) and Hariani et al. (2022). Similarly, studies in Sub-Saharan Africa, including research by Salahuddin et al. (2019), indicate that industrialization, though crucial for economic development, often leads to increased CO2 emissions due to outdated industrial processes and technologies.

In Uganda, the findings align with those of Appiah et al. (2019) and Okillong and Luwedde (2023), who reported a positive and significant effect of industrialization on CO2 emissions. These studies emphasize that industrial growth, while essential for economic development, exacerbates environmental degradation through increased carbon emissions. The increase in CO2 emissions associated with MVA reflects the broader trend observed in regions undergoing industrial expansion without corresponding advancements in energy efficiency and sustainable practices. Therefore, the observed positive relationship between MVA and CO2 emissions in Uganda can be attributed to the energy-intensive nature of manufacturing processes and the prevalent use of fossil fuels, highlighting the urgent need for policies promoting cleaner technologies and sustainable industrial practices.

4.5.3 Discussion Of findings on the effect of Urban population on CO2 emission in Uganda

The empirical analysis reveals a significant negative relationship between the urban population (LNUP) and CO2 emissions (LNCO2E) in Uganda, as indicated by a coefficient of -5.219857, with a standard error of 0.73370 and a t-statistic of -7.63418. This suggests that a 1% increase in the urban population corresponds to a 5.22% decrease in CO2 emissions. This statistically significant finding at the 5% level indicates that urban population growth in Uganda is associated with reduced CO2 emissions. This counterintuitive result can be attributed to several factors including increased urban hydro-electricity coverage, the growth in the uptake of solar power technologies, and effective government energy-saving campaigns.

One primary reason for this negative relationship is the significant increase in urban hydro-electricity coverage facilitated by UMEME, Uganda's primary electricity distribution company. Over the years, UMEME has expanded its customer base from 280,000 to 1.2 million, marking a growth rate in connections of 138% as of 2018. This expansion has significantly reduced the reliance on traditional biomass fuels such as charcoal and firewood in urban and peri-urban areas. The shift from biomass to hydro-electricity, a cleaner energy source, contributes to the reduction in CO2 emissions, providing a plausible explanation for the observed decrease in emissions despite the growing urban population.

Additionally, the growth in the uptake of solar power technologies and the government's aggressive energy-saving campaigns have further reduced the demand for charcoal and firewood. The Government of Uganda has recently distributed 10,000 gas cylinders and burners to households in Kampala, Wakiso, and Mukono, and continues to subsidize and distribute cylinders, cooking gas, and burners through partners like Total Energies, Starbex International, and Vivo Energy. These initiatives have significantly lessened the pressure on biomass fuel demand in urban areas, thus contributing to lower CO2 emissions. Furthermore, the launch of the 'Fumbalive' campaign in 2020 by the Uganda Ministry of Energy and Mineral Development, in collaboration with the Global Alliance for Clean Cookstoves and the Uganda National Alliance of Clean Cookstoves (UNACC), has encouraged the adoption of improved cookstoves. This campaign promotes energy-saving cooking practices, further supporting the observed negative effect of urban population growth on CO2 emissions.

The current findings align with the Environmental Kuznets Curve (EKC) hypothesis, as suggested by Liu and Bae (2018), which posits that emissions rise during the early stages of urbanization but decline as urban areas mature and adopt sustainable practices. This pattern is reflected in Uganda's urban centers, where increased efficiencies and the adoption of cleaner technologies have led to reduced emissions. Conversely, the results contrast with the findings of Wang et al. (2014) and Fragkias et al. (2017), who identified a direct correlation between urbanization and increased CO2 emissions due to higher energy consumption and transportation needs. However, the context-dependent nature of the relationship, as discussed by Xu and Lin (2015) and Zheng et al. (2023), underscores the importance of specific urban policies and technological advancements in shaping the environmental outcomes of urbanization.

Overall, the significant negative impact of urban population growth on CO2 emissions in Uganda highlights the crucial role of energy policy, technological adoption, and urban planning in mitigating environmental impacts. The empirical literature supports these findings, emphasizing the importance of sustainable urban development practices in achieving environmental sustainability amid urban growth.

4.5.4 Discussion of findings on the effect of Gross Domestic Product per capita on CO2 emissions in Uganda

The empirical analysis reveals a significant negative relationship between GDP per capita (LNGDPc) and CO2 emissions (LNCO2E) in Uganda, indicated by a coefficient of -0.828100, a standard error of 0.10847, and a t-statistic of -7.11444. This suggests that a 1% increase in GDP per capita corresponds to a 0.83% decrease in CO2 emissions, with the result being statistically significant at the 5% level. This finding implies that as GDP per capita increases, CO2 emissions decrease, potentially due to the adoption of cleaner technologies and more efficient production processes as income levels rise.

This observed negative relationship aligns with the Environmental Kuznets Curve (EKC) hypothesis, which posits that as an economy grows, CO2 emissions initially increase but eventually decrease as the economy transitions to more sustainable practices. This pattern has been documented in OECD countries, where technological advancements and stringent environmental policies have led to a decoupling of economic growth from CO2 emissions (Le Quéré et al., 2020). The decline in emissions in these countries is attributed to improved energy efficiency and a shift towards service-based economies (Kutlu and Örün, 2023). Similarly, Uganda may be experiencing the early stages of this transition, where increased income levels facilitate investments in cleaner technologies and more efficient energy use, thus reducing CO2 emissions.

Contrastingly, the ASEAN region presents a different scenario where rapid industrialization and urbanization have significantly increased CO2 emissions, as economic growth in these countries is closely tied to energy consumption patterns and reliance on fossil fuels (Batool et al., 2022). This suggests that ASEAN countries are still in the upward phase of the EKC, where economic growth exacerbates environmental degradation due to insufficient environmental regulations. In Sub-Saharan Africa, including East Africa, the relationship between GDP per capita and CO2 emissions is less pronounced due to lower levels of industrialization and economic activity. However, as these regions develop, the potential for increased emissions is significant if development follows the same carbon-intensive paths seen elsewhere (Gebrechorkos et al., 2023; Namahoro et al., 2021).

In Uganda specifically, the relationship between GDP per capita and CO2 emissions reflects broader regional trends. While current emissions are relatively low due to the predominantly agrarian economy, recent developments in manufacturing and services sectors have begun to impact emissions (Kiggundu et al., 2022). However, the counterintuitive finding of a negative relationship in the current study, compared to previous studies such as Otim et al. (2022),Appiah et al. (2019) may be due to differences in sample periods and the regressors included. Otim et al. (2022) used a sample period from 1986 to 2018 and considered only two predictors (energy consumption and GDP), whereas the current study analysed the determinants of CO2 emissions for the period from 1990 to 2020, focusing on four predictors: the annual deforestation rate, manufacturing value added, urban population, and GDP per capita. On the other hand, Appiah et al. (2019) used 1990-2014 as the sample period and included energy intensity as one of the predictor variables unlike the current study. Additionally, Appiah et al. (2019) also used industrial value added as a proxy for indusrialisation whereas the current study used manufacturing value added to proxy indusrialisation. More over while Appiah et al. (2019) used the autoregressive distributed lag approach to model CO2 emissions, the current study employed the vector error correction model.Thus methodological, sample period, variable differences may capture additional dynamics that influence CO2 emissions, leading to the observed negative relationship.

Overall, the significant negative impact of GDP per capita on CO2 emissions in Uganda underscores the potential for sustainable development practices to decouple economic growth from environmental degradation. The empirical literature supports these findings, emphasizing the importance of technological advancements and effective environmental policies in achieving sustainable economic growth.

CHAPTER FIVE

SUMMARY OF FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter summarises the findings, conclusions, and recommendations from the analyses conducted in the preceding chapters. The study employed the Vector Error Correction Model (VECM) to examine the determinants of CO2 emissions in Uganda, with a focus on data spanning from 1990 to 2020. By analysing the effect of annual deforestation rate, manufacturing value added, urban population and domestic product per capita on CO2 emissions, the study aimed to uncover the underlying dynamics influencing price levels in Uganda. This chapter synthesizes the key results derived from the empirical investigation, draws overarching conclusions based on the evidence, and offers practical recommendations for policymakers and stakeholders. The insights gained from this study are intended to contribute to a deeper understanding of inflationary trends and to inform strategies for managing inflation in Uganda effectively.

5.2 Summary of Findings

The main objective of this study was to examine the determinants of CO2 emissions in Uganda. This objective was met by testing the following null hypotheses:

H_0-1. There is no significant effect of annual deforestation rate on CO2 emissions in Uganda.

H_0-2. There is no significant effect of manufacturing value added on CO2 emissions in Uganda.

H_0-3. There is no significant effect of urban population on CO2 emissions in Uganda.

H_0-4. There is no significant effect of DGP per capita on CO2 emissions in Uganda

The findings are summarized as follows:

5.2.1The Effect of the Annual Deforestation Rate (LNADR) on CO2 Emissions in Uganda

The analysis indicated a significant positive relationship between the annual deforestation rate and CO2 emissions in Uganda. This relationship suggests that increases in deforestation are strongly associated with increases in CO2 emissions. The robustness of this finding was confirmed by the statistical significance of the relationship, highlighting the substantial impact of deforestation on the country's carbon emissions.

5.2.2The Effect of Manufacturing Value Added on CO2 Emissions in Uganda:

The study revealed a significant positive relationship between manufacturing value added and CO2 emissions. This finding indicates that as the manufacturing sector expands, there is a corresponding increase in CO2 emissions. The statistical significance of this relationship underscores the environmental impact of industrial growth in Uganda, suggesting that manufacturing activities are a considerable source of carbon emissions.

5.2.3 The Effect of Urban Population (LNUP) on CO2 Emissions in Uganda

Contrary to apriori expectations, the analysis found a significant negative relationship between urban population growth and CO2 emissions. This result implies that increases in the urban population are associated with decreases in CO2 emissions. This inverse relationship may be attributed to greater efficiency or effective environmental policies in urban areas, which mitigate the impact of population growth on emissions.

5.2.4 The Effect of Gross Domestic Product per Capita (LNGDPc) on CO2 Emissions in Uganda

The findings indicate a significant negative relationship between GDP per capita and CO2 emissions. This suggests that as GDP per capita increases, CO2 emissions decrease, potentially due to the adoption of cleaner technologies and more efficient production processes as income levels rise. The statistical significance of this relationship highlights the potential for economic growth to be coupled with environmental sustainability in Uganda.

5.3 Conclusions of the study

5.3.1 Conclusion on the Effect of annua deforestation rate on CO2 emissions in Uganda.

The analysis demonstrated a significant positive relationship between the annual deforestation rate and CO2 emissions in Uganda. This finding underscores the profound impact deforestation has on increasing CO2 emissions, corroborating the global understanding that forests serve as vital carbon sinks. The substantial increase in CO2 emissions associated with a rise in deforestation rates highlights the critical need for robust forest management and conservation strategies in Uganda. These results are consistent with theoretical and empirical evidence from various regions, reinforcing the importance of preserving forest cover to mitigate environmental degradation and support long-term sustainability.

5.3.2 Conclusion on the Effect of Manufacturing Value Added on CO_2 Emissions in Uganda

The analysis reveals a significant positive relationship between Manufacturing Value Added (MVA) and CO_2 emissions in Uganda, indicating that an increase in MVA results in higher CO_2 emissions. This finding highlights the environmental impact of industrial growth, consistent with global and regional trends. In various contexts, including OECD countries, ASEAN, and Sub-Saharan Africa, industrial activities contribute significantly to CO_2 emissions due to reliance on fossil fuels and outdated technologies. In Uganda, this aligns with previous studies that emphasize the dual role of industrialization in economic development and environmental degradation. The results underscore the need for Uganda to adopt cleaner technologies and sustainable industrial practices to address the adverse effects of industrial growth on CO_2 emissions.

5.3.3 Conclusion on the Effect of urban population on CO_2 Emissions in Uganda

The findings of this analysis underscore a notable negative relationship between urban population growth and CO_2 emissions in Uganda, suggesting that increases in urban dwellers can lead to a decrease in emissions. This counterintuitive result can largely be attributed to the expanded access to clean energy sources, particularly hydro-electricity, as well as the increased uptake of solar power technologies and government initiatives promoting energy efficiency. These factors collectively reduce reliance on traditional biomass fuels, contributing to lower emissions. Additionally, the study aligns with the Environmental Kuznets Curve hypothesis, indicating that while initial urbanization might lead to increased emissions, sustainable practices eventually prevail as urban areas mature. Overall, this evidence highlights the significance of effective energy policies, technological advancements, and strategic urban planning in shaping more sustainable environmental outcomes as Uganda continues to urbanize.

5.3.4 Conclusion on the Effect of GDP per capita on CO_2 Emissions in Uganda

In summary, the analysis demonstrates a noteworthy negative relationship between GDP per capita and CO_2 emissions in Uganda, suggesting that as economic conditions improve, emissions tend to decrease. This pattern aligns with the Environmental Kuznets Curve (EKC) hypothesis, indicating that Uganda may be at a transitional stage where economic growth is increasingly coupled with cleaner technologies and sustainable practices. Unlike regions such as ASEAN, which are experiencing increased emissions due to rapid industrialization, Uganda's relatively low emissions reflect its agrarian economy and emerging manufacturing sector. The findings indicate that growth is not simply an avenue for increased environmental degradation but can also present opportunities for implementing more effective environmental strategies. Overall, Uganda's experience illustrates the potential for achieving sustainable development through the integration of economic growth with environmental considerations, emphasizing the need for continued investment in cleaner technologies and sustainable practices as GDP per capita rises.

5.4 Limitations of the study

Despite the valuable insights provided by this research on CO2 emissions and their determinants in Uganda from 1990 to 2020, several limitations warrant consideration.

A primary limitation is the restricted availability of time series data, which necessitated a 30-year timeframe for analysis. This brevity can significantly impact the robustness of time series studies, as shorter periods may limit the sample size and reduce the generalizability of findings. The limited timeframe can also hinder the ability to effectively test for unit roots, making it challenging to reject the null hypothesis when it is indeed false (Weigend, 2018). To counteract these limitations, the study enhanced the dataset by converting annual data into quarterly intervals, thereby increasing the sample size and providing a more granular analysis.

Another limitation lies in the temporal scope of the study, which spans from 1990 to 2020. While this period offers a substantial dataset, it may not adequately reflect the most recent economic shifts or historical trends. The dynamics of economic conditions and policy impacts can change swiftly, and the exclusion of data beyond 2020 may diminish the relevance of the findings in contemporary policy discussions. To address this, the study concentrated on identifying persistent macroeconomic trends that are likely to remain significant, despite the omission of more current data.

Methodologically, the study's reliance on the Vector Error Correction Model (VECM) presents certain constraints. While VECM is effective for capturing both long-term and short-term relationships among variables, it operates under the assumption of linearity, potentially overlooking non-linear relationships or structural breaks in the data. Given the complexity of economic interactions, which are often influenced by multifaceted factors, this could lead to an incomplete understanding of the dynamics at play. To mitigate this, the research included robustness checks, such as alternative model specifications and diagnostic tests, to validate the assumptions and outcomes of the VECM.

Additionally, while the study successfully identified significant relationships among CO_2 emissions and its macroeconomic determinants, it did not delve into external factors like global economic conditions, geopolitical events, or climate change, which may also influence CO_2 emission dynamics. The omission of these external influences could result in a partial understanding of the factors affecting CO_2 emissions in Uganda. The study acknowledged these gaps in the discussion and proposed future research avenues to incorporate these external variables.

Time constraints also posed a challenge, as the research period was relatively short compared to the extensive demands of data collection, analysis, and interpretation. This limitation may have restricted the depth of the analysis and the exploration of additional variables or methodologies that could have enhanced the study. A more extended research timeframe could have facilitated a more comprehensive examination of the data and allowed for the inclusion of more rigorous checks and balances. To address this, the study implemented efficient research methodologies and time management strategies to ensure thorough analysis within the available timeframe. Future research endeavors with extended periods could yield even deeper insights.

Finally, the focus on Uganda inherently limits the generalizability of the findings to other contexts. While the results provide critical insights into the determinants of CO_2 emissions in Uganda, different countries possess unique economic structures, policy environments, and external influences that could result in divergent CO_2 emission dynamics. Therefore, caution is advised when extrapolating these findings to other settings without considering the specific economic conditions and policy frameworks in those locales. The study highlighted Uganda's unique contextual factors and recommended that similar investigations be conducted in other countries to validate and compare findings.

While this study offers important insights into the macroeconomic determinants of CO_2 emissions in Uganda, it is essential to recognize these limitations when interpreting the findings and considering their implications for policy and further research.

5.5 Recommendations of the study

Based on the findings and conclusions of this study, several recommendations are proposed to enhance economic growth in Uganda through financial development and mobile phone penetration.

5.5.1 Recommendation on the Effect of Annual Deforestation Rate on CO_2 Emissions in Uganda

Given the significant positive relationship between deforestation and CO2 emissions, it is crucial to implement robust forest conservation and management strategies. The Ugandan government should prioritize the enforcement of existing laws that protect forested areas and expand reforestation programs. Additionally, promoting sustainable agricultural practices that reduce the need for land clearance could help curb the annual deforestation rate. Awareness campaigns and community involvement are also essential to ensure the long-term success of these initiatives.

5.5.2 Recommendation on the Effect of Manufacturing Value Added on CO2 Emissions in Uganda

The positive correlation between manufacturing growth and CO2 emissions indicates the need for adopting cleaner technologies and enhancing energy efficiency within the industrial sector. The government should incentivize the transition to greener manufacturing processes through tax breaks, subsidies, and technical support for industries that adopt low-carbon technologies. Moreover, policies encouraging the development and use of renewable energy sources in manufacturing can significantly reduce the sector's carbon footprint.

5.5.3 Recommendation on the Effect of Urban Population on CO2 Emissions in Uganda

The inverse relationship between urban population growth and CO2 emissions suggests that urbanization, if managed effectively, can lead to environmental benefits. It is recommended that urban planning policies focus on enhancing public transportation, expanding access to clean energy, and promoting energy-efficient building designs. Additionally, investing in sustainable urban infrastructure and implementing policies that reduce reliance on fossil fuels in cities can further leverage the environmental benefits associated with urban population growth.

5.5.4 Recommendation on the Effect of GDP per Capita on CO2 Emissions in Uganda

The negative relationship between GDP per capita and CO2 emissions highlights the potential for economic growth to be aligned with environmental sustainability. Policymakers should continue to promote economic policies that encourage investment in clean technologies and sustainable practices. This can be achieved through financial incentives for businesses that prioritize environmental responsibility and by supporting research and development in green technologies. Furthermore, raising public awareness about the environmental impacts of consumption and encouraging sustainable lifestyle choices can complement these efforts.

Based on the findings and limitations of this study on CO2 emissions and their determinants in Uganda, several additional recommendations are proposed to enhance understanding and inform policy decisions:

Enhance Data Collection Efforts

To improve the robustness of future research, it is crucial to enhance the collection of time series data on CO2 emissions and their determinants. This includes investing in comprehensive data systems that capture not only annual but also quarterly and monthly data across various sectors. Collaboration with governmental and non-governmental organizations can facilitate the gathering of high-quality data on deforestation rates, manufacturing outputs, urban demographics, and economic indicators.

Expand Temporal Scope of Research

Future studies should consider extending the temporal scope beyond 2020 to capture more recent economic developments and their impacts on CO2 emissions. Incorporating data from subsequent years will allow researchers to analyze the effects of emerging trends, policies, and global events, thus providing a more current and relevant context for understanding emission dynamics.

Adopt Diverse Methodological Approaches

Researchers are encouraged to explore diverse methodological frameworks that account for non-linear relationships and structural breaks in the data. Techniques such as machine learning models or non-linear regression analysis could provide deeper insights into the complex interactions among variables influencing CO2 emissions. Additionally, integrating qualitative methods could enrich the analysis by incorporating stakeholder perspectives on environmental policies and practices.

Incorporate External Influences

Future research should aim to include external factors such as global economic conditions, geopolitical influences, and climate variability in the analysis of CO2 emissions. By acknowledging and integrating these external variables, researchers can develop a more comprehensive understanding of the multifaceted drivers of emissions, leading to more effective policy recommendations.

Focus on Policy Implications

Given the significant relationships identified between CO2 emissions and economic determinants, policymakers should prioritize the development of sustainable economic policies that balance industrial growth with environmental protection. This includes promoting green technologies, sustainable manufacturing practices, and urban planning initiatives that reduce emissions while fostering economic development.

Conduct Comparative Studies

To enhance the generalizability of findings, comparative studies across different countries or regions with similar economic structures but varying environmental policies should be conducted. Such research could help identify best practices and effective strategies for managing CO2 emissions while considering local contexts.

Engage Stakeholders in Policy Formulation

It is essential to involve various stakeholders, including local communities, businesses, and environmental organizations, in the formulation of policies aimed at reducing CO2 emissions. Engaging these groups can foster collaboration and ensure that policies are well-informed and widely supported, ultimately leading to more successful implementation.

Promote Public Awareness and Education

Raising public awareness about the impact of CO2 emissions and the importance of sustainable practices is vital. Educational campaigns can empower citizens to participate in emission reduction efforts, such as advocating for reforestation, supporting local sustainable businesses, and adopting eco-friendly practices in their daily lives. By implementing these recommendations, future research can contribute to a more nuanced understanding of CO2 emissions in Uganda and inform effective strategies for sustainable development and environmental stewardship.

5.6 Contributions of the Study

This study makes several important contributions to the understanding of the determinants of CO2 emissions in Uganda, providing insights that are valuable for both academic research and policy formulation.

5.6.1 Empirical Insights on Deforestation and CO2 Emissions

One of the key contributions of this study is its empirical analysis of the relationship between deforestation and CO_2 emissions in Uganda. By demonstrating a significant positive correlation, the study highlights the critical impact of deforestation on environmental degradation in Uganda. This finding contributes to the broader literature on environmental economics by providing specific evidence from a developing country context, thereby enriching the global understanding of the environmental consequences of land-use changes.

5.6.2 Industrial Growth and Environmental Impact

The study also contributes to the discourse on the environmental implications of industrialization in Uganda. By establishing a positive relationship between manufacturing value added and CO_2 emissions, the research underscores the environmental costs associated with industrial expansion. This finding is particularly relevant for policymakers and stakeholders in developing economies, offering empirical evidence that can inform strategies to balance industrial growth with environmental sustainability.

5.6.3 Urbanization and CO2 Emissions

Another significant contribution of this study is its analysis of the relationship between urban population growth and CO_2 emissions, which revealed a surprising inverse correlation. This counterintuitive finding challenges conventional wisdom and suggests that urbanization, when coupled with effective environmental policies, can lead to reductions in CO_2 emissions. This contribution is valuable for urban planners and policymakers, highlighting the potential of urbanization to contribute positively to environmental outcomes if managed appropriately.

5.6.4 Economic Growth and Environmental Sustainability

The study provides evidence supporting the Environmental Kuznets Curve hypothesis in the context of Uganda, showing that higher GDP per capita is associated with lower CO_2 emissions. This finding contributes to the ongoing debate on the relationship between economic growth and environmental sustainability, particularly in developing countries. It underscores the potential for economic development to be aligned with environmental goals, offering a hopeful perspective on the possibility of achieving sustainable development.

5.6.5 Methodological Contributions

Methodologically, the study contributes to the literature by applying a Vector Error Correction Model (VECM) to analyze the long-term and short-term relationships between CO_2 emissions and their determinants in Uganda. The use of VECM in this context provides a robust framework for understanding the dynamic interactions between economic variables and environmental outcomes, making a methodological contribution to studies in environmental economics.

Overall, this study enriches the understanding of the complex relationships between economic development, urbanization, industrialization, and environmental sustainability in Uganda. It provides valuable insights for both scholars and policymakers, offering evidence-based recommendations that can guide future research and policy initiatives aimed at reducing CO_2 emissions and promoting sustainable development.

5.7 Areas for further research

Building upon the findings and limitations of this study, several areas for future research are identified to further deepen the understanding of CO_2 emissions and their determinants in Uganda.

5.7.1 Expanding Temporal Scope and Data Granularity

Future research should focus on expanding the temporal scope beyond the year 2020 to incorporate more recent data and capture the effects of new economic policies, global events, and technological advancements on CO_2 emissions. Additionally, increasing the granularity of data collection to include monthly or quarterly intervals can provide more detailed insights into the temporal dynamics of CO_2 emissions and allow for more precise modeling of the relationships between economic activities and environmental outcomes.

5.7.2 Investigating Non-Linear Relationships and Structural Breaks

Given the complexity of the interactions between economic growth, industrialization, urbanization, and environmental sustainability, future studies should explore non-linear relationships and potential structural breaks within the data. Employing advanced econometric techniques such as non-linear regression models, threshold models, or machine learning algorithms could reveal hidden patterns and provide a more nuanced understanding of the determinants of CO_2 emissions.

5.7.3 Incorporating External and Contextual Factors

Further research should aim to incorporate external factors such as global economic conditions, geopolitical shifts, and climate change impacts into the analysis of CO_2 emissions in Uganda. By integrating these broader influences, future studies can offer a more comprehensive view of the determinants of emissions and their interactions with both domestic and international developments.

5.7.4 Comparative Analysis Across Regions and Sectors

Conducting comparative studies across different regions within Uganda or across countries with similar economic profiles could provide valuable insights into how varying policy environments and economic structures influence CO_2 emissions. Additionally, sector-specific analyses, particularly focusing on agriculture, energy, and transportation, could help identify targeted strategies for reducing emissions within those key areas.

5.7.5 Longitudinal Studies on Policy Impacts

There is a need for longitudinal studies that track the impact of specific environmental policies, such as reforestation initiatives or clean energy adoption programs, on CO_2 emissions over time. Such studies would provide critical evidence on the effectiveness of these interventions and offer guidance on best practices for policymakers aiming to mitigate emissions in Uganda.

5.7.6 Exploring the Role of Technology and Innovation

Future research should explore the role of technological advancements and innovation in reducing CO_2 emissions in Uganda. This could include studies on the adoption of renewable energy technologies, the efficiency of industrial processes, and the potential of digital technologies to optimize resource use and minimize environmental impact. Understanding the barriers to and drivers of technology adoption could help formulate strategies to accelerate the transition to a low-carbon economy.

5.7.7 Public Perception and Behavioral Studies

Research into public perceptions and behaviours regarding environmental issues and CO_2 emissions could provide valuable insights for designing effective awareness campaigns and policy interventions. Understanding the socio-cultural factors that influence public attitudes towards deforestation, urbanization, and energy use can help tailor policies that are both effective and socially acceptable.

By pursuing these areas of research, scholars can contribute to a more detailed and actionable understanding of the factors driving CO_2 emissions in Uganda, thereby informing more effective strategies for achieving sustainable development and environmental protection.

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APPENDIX 1: **Table 4.9 Error Correction Estimates for the determinants of CO_2 emissions in Uganda (1990-2020**)

Error Correction:	D(LNCO2E)	D(LNADR)	D(LNMVA)	D(LNUP)	D(LNGDPC)
COINTEQ1	-0.056730	-0.004461	-0.103869	0.000321	-0.000350
	(0.01945)	(0.00206)	(0.04083)	(0.00049)	(0.02851)
	[-2.91632]	[-2.17016]	[-2.54372]	[0.65162]	[-0.01229]
D(LNCO2E(-1))	0.742333	-0.009421	-0.196895	0.001891	-0.064646
	(0.10829)	(0.01144)	(0.22731)	(0.00274)	(0.15870)
	[6.85509]	[-0.82336]	[-0.86619]	[0.69045]	[-0.40736]
D(LNCO2E(-2))	0.017967	0.001670	0.032520	-5.95E-06	-0.003767
	(0.13640)	(0.01441)	(0.28633)	(0.00345)	(0.19990)
	[0.13172]	[0.11589]	[0.11358]	[-0.00173]	[-0.01884]
D(LNCO2E(-3))	-0.136907	-0.005106	-0.062449	0.001056	-0.192396
	(0.10638)	(0.01124)	(0.22330)	(0.00269)	(0.15590)
	[-1.28697]	[-0.45429]	[-0.27966]	[0.39257]	[-1.23412]
D(LNADR(-1))	0.356881	0.634092	-2.438436	0.006775	-1.746513
	(1.01209)	(0.10694)	(2.12449)	(0.02559)	(1.48320)
	[0.35262]	[5.92929]	[-1.14777]	[0.26474]	[-1.17753]
D(LNADR(-2))	0.573040	0.045761	1.012657	-0.002789	-0.045901
	(1.28150)	(0.13541)	(2.69002)	(0.03240)	(1.87802)
	[0.44716]	[0.33795]	[0.37645]	[-0.08606]	[-0.02444]
D(LNADR(-3))	1.196955	-0.351615	-1.622595	-0.004949	-2.332454
	(1.10129)	(0.11637)	(2.31175)	(0.02785)	(1.61393)
	[1.08686]	[-3.02156]	[-0.70189]	[-0.17771]	[-1.44520]
D(LNMVA(-1))	-0.028558	-0.001897	0.694129	-0.000336	-0.002912
	(0.05797)	(0.00613)	(0.12169)	(0.00147)	(0.08496)
	[-0.49261]	[-0.30962]	[5.70401]	[-0.22945]	[-0.03427]
D(LNMVA(-2))	0.003160	-1.45E-06	0.022750	-6.56E-05	0.005933
	(0.07173)	(0.00758)	(0.15056)	(0.00181)	(0.10511)
	[0.04406]	[-0.00019]	[0.15110]	[-0.03615]	[0.05644]
D(LNMVA(-3))	0.005262	0.006065	-0.098940	-1.68E-05	-0.039727
	(0.05703)	(0.00603)	(0.11972)	(0.00144)	(0.08358)
	[0.09226]	[1.00637]	[-0.82642]	[-0.01166]	[-0.47530]
D(LNUP(-1))	2.082828	0.142847	-0.192749	0.510132	-1.597775
	(3.78106)	(0.39953)	(7.93690)	(0.09561)	(5.54110)

	[0.55086]	[0.35754]	[-0.02429]	[5.33568]	[-0.28835]
D(LNUP(-2))	0.987451	0.074700	2.184475	-0.055864	-0.290375
	(4.28120)	(0.45237)	(8.98675)	(0.10825)	(6.27404)
	[0.23065]	[0.16513]	[0.24308]	[-0.51605]	[-0.04628]
D(LNUP(-3))	2.518763	0.211709	9.768259	0.299703	2.189554
	(3.64686)	(0.38535)	(7.65521)	(0.09221)	(5.34443)
	[0.69067]	[0.54940]	[1.27603]	[3.25007]	[0.40969]
D(LNGDPC(-1))	0.017504	-0.001820	0.013873	3.07E-05	0.808544
	(0.08232)	(0.00870)	(0.17280)	(0.00208)	(0.12064)
	[0.21263]	[-0.20927]	[0.08028]	[0.01477]	[6.70205]
D(LNGDPC(-2))	-0.032266	-0.002704	-0.051997	9.05E-05	0.004138
	(0.10751)	(0.01136)	(0.22568)	(0.00272)	(0.15756)
	[-0.30012]	[-0.23807]	[-0.23040]	[0.03329]	[0.02626]
D(LNGDPC(-3))	-0.030998	-0.002052	0.033657	-0.000148	0.063457
	(0.08900)	(0.00940)	(0.18682)	(0.00225)	(0.13043)
	[-0.34829]	[-0.21821]	[0.18015]	[-0.06570]	[0.48652]
C	-0.083425	-0.003832	-0.156940	0.003553	0.016234
	(0.04862)	(0.00514)	(0.10206)	(0.00123)	(0.07126)
	[-1.71578]	[-0.74576]	[-1.53766]	[2.88970]	[0.22783]
R-squared	0.643517	0.505978	0.594979	0.633447	0.726549
Adj. R-squared	0.588141	0.429237	0.532063	0.576506	0.684071
Sum sq. resids	0.018433	0.000206	0.081223	1.18E-05	0.039588
S.E. equation	0.013378	0.001414	0.028081	0.000338	0.019605
F-statistic	11.62085	6.593306	9.456719	11.12474	17.10421
Log likelihood	356.5929	626.2903	267.6106	797.8937	310.7303
Akaike AIC	-5.659881	-10.15484	-4.176843	-13.01490	-4.895505
Schwarz SC	-5.264986	-9.759944	-3.781948	-12.62000	-4.500610
Mean dependent	0.015973	0.003407	0.009120	0.014757	0.012271
S.D. dependent	0.020845	0.001871	0.041051	0.000520	0.034879

Determinant resid covariance (dof adj.)	5.07E-24
Determinant resid covariance	2.36E-24
Log likelihood	2412.770
Akaike information criterion	-38.71283
Schwarz criterion	-36.62221
Number of coefficients	90

Source: Author's analysis of WDI data

APPENDIX 2: ANNUAL SERIES FOR CO2 EMISSIONS AND ITS DETERMINANTS IN UGANDA (ANNUAL DEFORESTATION RATE, MANUFACTURING VALUE ADDED, URBAN POPULATION AND GDP PER CAPITA

YEAR	CO2E	ADR	MVA	UP	GDPC
1990	790.0	1.154040	5.341026	1922173	244.7541
1991	810.0	1.167684	5.438036	2056398	182.7945
1992	820.0	1.181228	5.820887	2188421	151.9765
1993	820.0	1.194923	5.598406	2326622	165.4650
1994	730.0	1.211591	6.030380	2471224	198.2821
1995	960.0	1.224167	6.229189	2622274	278.3166
1996	1070.0	1.239573	7.147087	2779697	284.4568
1997	1130.0	1.255423	7.787954	2943834	286.5727
1998	1290.0	1.271400	8.281100	3116698	292.1695
1999	1320.0	1.293934	8.893208	3300326	257.6786
2000	1330.0	1.304152	7.098978	3496913	257.8296
2001	1350.0	1.321278	7.061989	3707368	235.8530
2002	1540.0	1.339056	7.354144	3932636	241.8689
2003	1620.0	1.358171	7.055684	4172736	250.6906
2004	1770.0	1.375884	6.364934	4427392	292.4727
2005	2230.0	1.395232	7.009316	4695306	330.6029
2006	2600.0	1.395463	7.090616	4978580	346.7685
2007	2940.0	1.433694	7.125823	5277759	401.7092
2008	3180.0	1.435013	7.306965	5594570	473.3028
2009	3410.0	1.477722	16.53152	5929787	799.9296
2010	3850.0	1.497497	16.81475	6285551	824.7377
2011	4160.0	1.526810	17.14687	6661208	837.0959
2012	3910.0	1.557268	16.72571	7058269	796.7111
2013	4270.0	1.570194	15.61664	7480857	819.7579
2014	4740.0	1.571553	15.52205	7937455	897.5097
2015	4860.0	1.620621	16.85192	8432534	864.1801
2016	5670.0	1.621321	16.29974	8970229	753.6844
2017	5840.0	1.658271	15.52300	9549002	766.1776
2018	6130.0	1.679982	15.75142	10158400	793.1281
2019	5943.0	1.709359	15.52010	10784514	823.0247
2020	5674.6	1.733953	15.89301	11414209	846.7672

APPENDIX 3: QUARTERLY TRANSFORMED SERIES FOR CO2 EMISSIONS AND ITS DETERMINANTS IN UGANDA (ANNUAL DEFORESTATION RATE, MANUFACTURING VALUE ADDED, URBAN POPULATION AND GDP PER CAPITA

QUARTER	LNCO2E	LNADR	LNMVA	LNUP	LNGDPC
1990Q1	6.672033	0.143268	1.675418	14.46897	5.500254
1990Q2	6.678342	0.146220	1.679948	14.48627	5.434875
1990Q3	6.684612	0.149163	1.684458	14.50329	5.364921
1990Q4	6.690842	0.152097	1.688948	14.52001	5.289702
1991Q1	6.697034	0.155023	1.693418	14.53647	5.208362
1991Q2	6.700116	0.157918	1.710865	14.55239	5.165300
1991Q3	6.703188	0.160805	1.728014	14.56806	5.120300
1991Q4	6.706251	0.163684	1.744873	14.58349	5.073178
1992Q1	6.709304	0.166554	1.761453	14.59869	5.023726
1992Q2	6.709304	0.169449	1.751851	14.61436	5.045672
1992Q3	6.709304	0.172335	1.742157	14.62978	5.067147
1992Q4	6.709304	0.175212	1.732368	14.64497	5.088170
1993Q1	6.709304	0.178082	1.722482	14.65993	5.108760
1993Q2	6.681482	0.181563	1.741588	14.67535	5.157153
1993Q3	6.652863	0.185032	1.760336	14.69053	5.203312
1993Q4	6.623401	0.188489	1.778739	14.70549	5.247433
1994Q1	6.593045	0.191934	1.796810	14.72022	5.289691
1994Q2	6.668863	0.194526	1.805018	14.73539	5.385828
1994Q3	6.739337	0.197111	1.813160	14.75033	5.473528
1994Q4	6.805169	0.199689	1.821235	14.76505	5.554153
1995Q1	6.866933	0.202260	1.829246	14.77955	5.628759
1995Q2	6.895176	0.205402	1.865422	14.79445	5.634260
1995Q3	6.922644	0.208533	1.900336	14.80913	5.639730
1995Q4	6.949377	0.211655	1.934071	14.82359	5.645170
1996Q1	6.975414	0.214767	1.966705	14.83785	5.650581
1996Q2	6.989335	0.217958	1.988874	14.85251	5.652439
1996Q3	7.003065	0.221140	2.010563	14.86695	5.654294
1996Q4	7.016610	0.224311	2.031791	14.88119	5.656145
1997Q1	7.029973	0.227472	2.052578	14.89522	5.657992
1997Q2	7.064759	0.230649	2.068285	14.90980	5.662863
1997Q3	7.098376	0.233815	2.083748	14.92416	5.667710
1997Q4	7.130899	0.236972	2.098976	14.93832	5.672534
1998Q1	7.162397	0.240118	2.113976	14.95228	5.677334
1998Q2	7.168195	0.244540	2.132286	14.96691	5.647377
1998Q3	7.173958	0.248941	2.150267	14.98132	5.616495
1998Q4	7.179689	0.253324	2.167931	14.99552	5.584628
1999Q1	7.185387	0.257687	2.185288	15.00953	5.551713
1999Q2	7.187279	0.259659	2.133533	15.02431	5.551860
1999Q3	7.189168	0.261628	2.078953	15.03888	5.552006
1999Q4	7.191053	0.263592	2.021221	15.05324	5.552152
2000Q1	7.192934	0.265553	1.959951	15.06739	5.552299
2000Q2	7.196687	0.268830	1.958647	15.08232	5.530759
2000Q3	7.200425	0.272097	1.957342	15.09704	5.508746

2000Q4	7.204149	0.275354	1.956035	15.11154	5.486236
2001Q1	7.207860	0.278599	1.954727	15.12583	5.463209
2001Q2	7.242440	0.281957	1.965016	15.14091	5.469565
2001Q3	7.275865	0.285304	1.975201	15.15576	5.475882
2001Q4	7.308208	0.288640	1.985283	15.17040	5.482158
2002Q1	7.339538	0.291965	1.995264	15.18482	5.488396
2002Q2	7.352441	0.295527	1.985066	15.19997	5.497473
2002Q3	7.365180	0.299077	1.974763	15.21489	5.506468
2002Q4	7.377759	0.302614	1.964353	15.22959	5.515383
2003Q1	7.390181	0.306139	1.953834	15.24408	5.524219
2003Q2	7.413066	0.309394	1.929054	15.25922	5.565042
2003Q3	7.435438	0.312639	1.903645	15.27414	5.604263
2003Q4	7.457321	0.315873	1.877573	15.28884	5.642003
2004Q1	7.478735	0.319097	1.850804	15.30332	5.678371
2004Q2	7.541683	0.322606	1.875799	15.31834	5.710444
2004Q3	7.600902	0.326103	1.900184	15.33313	5.741521
2004Q4	7.656810	0.329588	1.923989	15.34771	5.771660
2005Q1	7.709757	0.333060	1.947240	15.36207	5.800918
2005Q2	7.750399	0.333102	1.950136	15.37704	5.813068
2005Q3	7.789455	0.333144	1.953023	15.39179	5.825072
2005Q4	7.827042	0.333185	1.955902	15.40633	5.836934
2006Q1	7.863267	0.333227	1.958772	15.42066	5.848657
2006Q2	7.895436	0.340052	1.960013	15.43557	5.887502
2006Q3	7.926603	0.346832	1.961252	15.45026	5.924894
2006Q4	7.956827	0.353566	1.962489	15.46474	5.960938
2007Q1	7.986165	0.360255	1.963725	15.47901	5.995728
2007Q2	8.006368	0.360485	1.970060	15.49391	6.039320
2007Q3	8.026170	0.360714	1.976355	15.50858	6.081090
2007Q4	8.045588	0.360944	1.982611	15.52305	6.121186
2008Q1	8.064636	0.361174	1.988828	15.53731	6.159735
2008Q2	8.082557	0.368587	2.263127	15.55218	6.318895
2008Q3	8.100161	0.375945	2.478154	15.56683	6.456167
2008Q4	8.117462	0.383250	2.655028	15.58127	6.576850
2009Q1	8.134468	0.390502	2.805269	15.59550	6.684524
2009Q2	8.166216	0.393842	2.809543	15.61039	6.692247
2009Q3	8.196988	0.397171	2.813799	15.62506	6.699911
2009Q4	8.226841	0.400488	2.818036	15.63951	6.707517
2010Q1	8.255828	0.403795	2.822256	15.65376	6.715065
2010Q2	8.275758	0.408677	2.827182	15.66859	6.718804
2010Q3	8.295299	0.413535	2.832084	15.68321	6.722530
2010Q4	8.314465	0.418369	2.836962	15.69761	6.726241
2011Q1	8.333270	0.423181	2.841816	15.71181	6.729939
2011Q2	8.318132	0.428155	2.835656	15.72660	6.717804
2011Q3	8.302762	0.433105	2.829459	15.74118	6.705521
2011Q4	8.287151	0.438031	2.823222	15.75555	6.693085
2012Q1	8.271293	0.442933	2.816947	15.76971	6.680492
2012Q2	8.294050	0.445006	2.800231	15.78457	6.687698
2012Q3	8.316300	0.447075	2.783230	15.79921	6.694852
2012Q4	8.338067	0.449139	2.765936	15.81363	6.701956
2013Q1	8.359369	0.451199	2.748337	15.82786	6.709009
2013Q2	8.386515	0.451415	2.746822	15.84300	6.732444
2013Q3	8.412943	0.451632	2.745304	15.85792	6.755343
2013Q4	8.438691	0.451848	2.743784	15.87262	6.777728
2014Q1	8.463792	0.452064	2.742262	15.88710	6.799624
2014Q2	8.470102	0.459839	2.763455	15.90258	6.790297
2014Q3	8.476371	0.467555	2.784208	15.91781	6.780882
2014Q4	8.482602	0.475211	2.804539	15.93282	6.771377
2015Q1	8.488794	0.482809	2.824465	15.94761	6.761781

2015Q2	8.529616	0.482917	2.816239	15.96342	6.729294
2015Q3	8.568836	0.483025	2.807946	15.97899	6.695715
2015Q4	8.606577	0.483133	2.799583	15.99432	6.660970
2016Q1	8.642944	0.483241	2.791149	16.00942	6.624974
2016Q2	8.650412	0.488923	2.779164	16.02542	6.629109
2016Q3	8.657824	0.494572	2.767034	16.04117	6.633228
2016Q4	8.665182	0.500190	2.754754	16.05668	6.637329
2017Q1	8.672486	0.505776	2.742323	16.07195	6.641414
2017Q2	8.684824	0.509044	2.745995	16.08778	6.650169
2017Q3	8.697012	0.512301	2.749653	16.10336	6.658849
2017Q4	8.709052	0.515547	2.753299	16.11870	6.667453
2018Q1	8.720950	0.518783	2.756931	16.13381	6.675985
2018Q2	8.713294	0.523145	2.753252	16.14910	6.685364
2018Q3	8.705580	0.527489	2.749561	16.16416	6.694657
2018Q4	8.697805	0.531813	2.745855	16.17900	6.703863
2019Q1	8.689969	0.536119	2.742136	16.19362	6.712986
2019Q2	8.678615	0.539709	2.748125	16.20811	6.720172
2019Q3	8.667129	0.543287	2.754078	16.22240	6.727307
2019Q4	8.655511	0.546852	2.759996	16.23648	6.734391
2020Q1	8.643755	0.550404	2.765880	16.25037	6.741426
2020Q2	8.631860	0.553943	2.771728	16.26407	6.748411
2020Q3	8.619822	0.557470	2.777543	16.27758	6.755348
2020Q4	8.607637	0.560985	2.783325	16.29091	6.762237