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PhD RESEARCH WORK

On

The effects of human capital and infrastructural development on industrial sector growth in sub-Saharan African economies.

By

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The following competition award, conferences and publications emanated from this research investigation, namely:

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[1] Research Capacity Building Workshop-Promoting Research and Innovation in the University System 2021.

[2] **Keji Sunday. A., Mbonigaba, Josue and Akinola Gbenga. W.** *An Empirical Effect of Human Capital Skill Development on Industrial Sector Growth in SSA. A disaggregated System-GMM Approach, 26th – 27th April, 2023,* **Federal University Oye-Ekiti, Nigeria**.

[3] **Keji Sunday. A., Akinola Gbenga. W., and Mbonigaba, Josue.** *"A comparative analysis of the spillover effects from human capital skill and infrastructural development on industrial sector growth. 12th-14th September, 2023,* ***ESSA 2023 Biennial Conference, South Africa.***

Publications (Published, accepted and under review)

[3] **Keji Sunday. A., Mbonigaba, Josue and Akinola Gbenga. W.** "The economic effects of infrastructure investment on industrial sector growth in sub-Sahara Africa: A Disaggregated System-GMM Approach." A publication of the ***International Journal of Critical Infrastructures***. **Published after acceptance for publication on 07/01/2025.**

[4] **Keji Sunday. A., Akinola Gbenga. W. and Mbonigaba, Josue** *"A comparative analysis of the spillover effects from human capital skill and infrastructural development on industrial sector growth."* A publication of the ***Cogent Economics and Finance***. An excerpt from the objective of the thesis. **Published after acceptance for publication on 03/09/2024.**

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LIST OF ACRONYMS

ACRONYMS	DEFINITION OF TERMS
ACE	Access to Energy
ACT	Access to Transportation
AWP	Access to pure water
AYS	Average Year of Schooling
FDI	Foreign Direct Investment
GCF	Gross Capital Formation
GMM	Generalized Methods of Moment
HCS	Human Capital Skills
HOC	Household Consumption
IDO	Industrial Output
ICT	Information Technology
INF	Infrastructure
LER	Life Expectancy Rate
LBF	Labour Force
LIR	Literacy Rate
LPR	Labour Participation Rate
LSDV	Least Square Dummy Variable
OECD	Organization for Economic Cooperation and Development
SER	School Enrolment Rate
SSA	Sub Saharan Africa
TECH	Technology

LIST OF SYMBOLS AND NOTATIONS

List of Symbols Sign Notations

Latin small letter F with Hook	ƒ
Exma	ε
Alpha	α
Beta	β
Greek small letter delta	δ
Mu	μ
Theta	θ
Asterisk	*
Gamma	γ
Greek capital letter delta	Δ
Sigma	σ
Lamda	λ
Phi	Φ
small letter N retroflex Hook	ɳ

ABSTRACT

Fundamentally, Human Capital Skills and Infrastructural Development are expected to enhance Industrial Sector Growth in Sub-Saharan African Economies. However, evidence from the literature observed a paradox that requires further investigation. Consequently, this study examined factors determining industrial output growth in Sub-Saharan African Economies. The study investigated the comparative effects of human capital skills and infrastructural development on industrial output growth across four sub-regional economic blocs in 40 SSA countries between 1990 and 2022. Also, the study examined asymmetric and threshold effects of human capital skill and infrastructure on industrial output growth across the sub-regional economic blocs in SSA. The study hypothesised that (i) certain factors impact industrial output growth, (ii) human capital skills and infrastructural techs had comparative effects and significant effects on industrial output growth, (iii) there were asymmetric and threshold effects of human capital skills and infrastructural development on industrial output growth across sub-regional economic blocs in SSA.

A panel data analysis via trend, matrix correlation estimating techniques, and short-run and long-run dynamic systems from generalised methods of the moment (GMM) were adopted to achieve objective one. Trend analysis, Sub-sample analysis, Fixed Least Square Dummy Variable (LSDV) and short-run and long-run dynamic system GMM were adopted to achieve objective two. To achieve objective three, panel threshold regression and Non-linear Autoregressive Distributed Lags (NARDL) techniques were used. The outcomes from objective one showed that key measurement variables had short-run and long-run dynamic effects on industrial output growth in SSA. This implies that industrial output growth is path-dependent, indicating that the current level of a country's output growth strongly influences its future output growth. For example, factors like school enrolment rate, ICT, and average year of schooling were negative and statistically significant in impacting growth.

Consequently, the study recommended that authorities in SSA enact policies that would drive human capital skills and infrastructure development across the region. It was also suggested that individual sub-regions such as ECA, ECCAS, ECOWAS and SADC should draft sub-regional policy support unique to their sub-region to address specific and perennial problems militating against industrial output growth.

KEYWORDS: ***Comparative Effects*; *Human Capital; Infrastructure*; *Industrial Output***

CHAPTER ONE

INTRODUCTION

1.1 PREAMBLE

In recent times, individual sub-regions across the globe have strived to promote industrial output growth through varied means of productive inputs. For example, South Asia changed industrial production fortunes through massive infrastructural investment (Du, Zhang and Han, 2022). Sub-regions such as North America promoted industrial output growth through massive advancement in human capital skills and infrastructure (World Bank Development Index, 2023). However, the fortunes of advancing industrial output growth have remained mirage in sub-Saharan Africa (SSA) due to poor human capital skills and low infrastructure development (Akinlo, 2020; Keji, 2021; Amoah & Jehu-Appiah, 2022; World Bank Development Index, 2023).

To achieve the set objectives in the study, it is pertinent to examine the current poor human capital skills, dilapidated spread of infrastructure and slow industrial output growth in SSA. Firstly, the study examined factors determining industrial output growth in SSA. Secondly, the study investigated the comparative effect of human capital skills and infrastructure on industrial output growth across economic blocs (such as EAC ECCAS ECOWAS and SADC) in SSA. Lastly, the study examined the threshold and asymmetric effects of human capital skills and infrastructure on industrial output growth across sub-regional economic blocs in SSA.

This study identified factor inputs that determined industrial output growth in SSA. It was revealed that most of the factors identified significantly determined industrial output growth in the sub-region, while a few others were insignificant in influencing industrial output growth. Hence, they were dropped to pave the way for the second objective of the study.

The study achieved the second objective by assessing the comparative effects of human capital skills and infrastructure on industrial output growth across the sub-regional economic blocs in SSA. This was motivated to address individual sub-regional bloc-specific effects regarding slow industrial output growth. In this regard, the menace of slow industrial output growth can be addressed with respect to individual sub-regional comparative economic advantage and policy specifics relating to factor inputs. Consequently, this paved ways for the third objective in the study.

The study achieved the third objective by assessing the threshold effects of human capital skills and infrastructure on industrial output growth in SSA, to set certain trajectories for industrial output growth across the sub-region. These trajectories were meant to aid certain policy directions for addressing SSA's slow industrial output growth. Moreover, the asymmetric effects of human capital skills and infrastructure were investigated in relation to industrial output growth across individual economic blocs in SSA. This was to ascertain dual regimes' effects of human capital skills and infrastructure on industrial output growth across EAC ECCAS ECOWAS and SADC. In this regard, the asymmetric effects of human capital skills and infrastructure of individual sub-regional economic blocs' were established.

Consequently, outcomes from this study are expected to provide answers to the ongoing debates in the literature as to whether symmetric or asymmetric effects of human capital skills and infrastructure engender industrial output growth and, subsequently, industrial sector growth in SSA.

1.2 BACKGROUND TO THE STUDY

Improving output is the primary goal of any economy, especially during this period of global output rise, where human knowledge and infrastructural technology are the leading causes towards expanding general output growth (Friderichs, Keeton & Rogan, 2021; Du, Zhang & Han, 2022)**.** Therefore, developing industrial sector growth across the sub-Saharan African (SSA) region is pertinent since the sub-region economies form part of small open economies within the global village. Nevertheless, industrial output growth in SSA is far below the expected output level compared to other regions like Europe, America and Asia regarding knowledge-driven productive skill and high-tech infrastructural set-up (Okumoko, Omeje & Udoh, 2018; Akinlo, 2020; Keji, 2021). Notably, economic theorists such as Romer (1986;1990), Lucas (1988), Rebelo (1991) and Mankiw (1995) posited that emerging knowledge like human capital skill along with emerging technical progress such as infrastructural technology augment the production scale to yield increasing return to scale. Based on this theoretical assertion, the improved comparative effects of human capital skills and infrastructure advancement are expected to strengthen industrial output growth in SSA. However, evidence concerning this theoretical postulation suggests otherwise in the case of sub-Saharan Africa. For example, although there was limited knowledge linking human capital skills, infrastructure, and industrial output growth in SSA, the schematic evidence drawn from the recent World Bank Development Index (2022) in Figures 1.1, 1.2 and 2.4 regarding the background causes of slow industrial output growth in SSA showed that human capital skills and infrastructure indicators appeared not to cause the industrial sector growth in sub-Saharan Africa, as against the economic expectation. Also, in Figure 1.3, the general causes of those contractions in theoretical postulations were schematically illustrated. This contraction instead opens wide gaps that draw much to be investigated. In view of this, it is pertinent to examine the wide disconnections between industrial output growth, human capital skills development and infrastructural development in the case of SSA because industrial sector growth requires higher skills in innovation and creativity alongside technology-driven infrastructure.

Figure 1.1 disclosed the inter-region comparison that elucidated the severity of the problems associated with slow industrial sector growth in SSA, as the sub-region accounted for the lowest output growth among the other regions. Over the years, the schematic evidence, as indicated in Figure 1.1 below from the World Bank data, suggests that the sub-Sahara Africa region has remained slow regarding industrial output values. It is revealed that the industrial output of East Asia (ESA) rose from behind to a distance high in recent years, which confirms the convergence theory argument that developing economies need to proliferate regarding productivity to converge with the developed economies. North America (NA) and the European Union (EU) moved up the ladder, respectively, while SSA remained at the bottom level throughout the years under review. Consequently, this evidence showed slow industrial sector growth compared to other regions regarding low human capital skills and poor infrastructural spread in SSA.

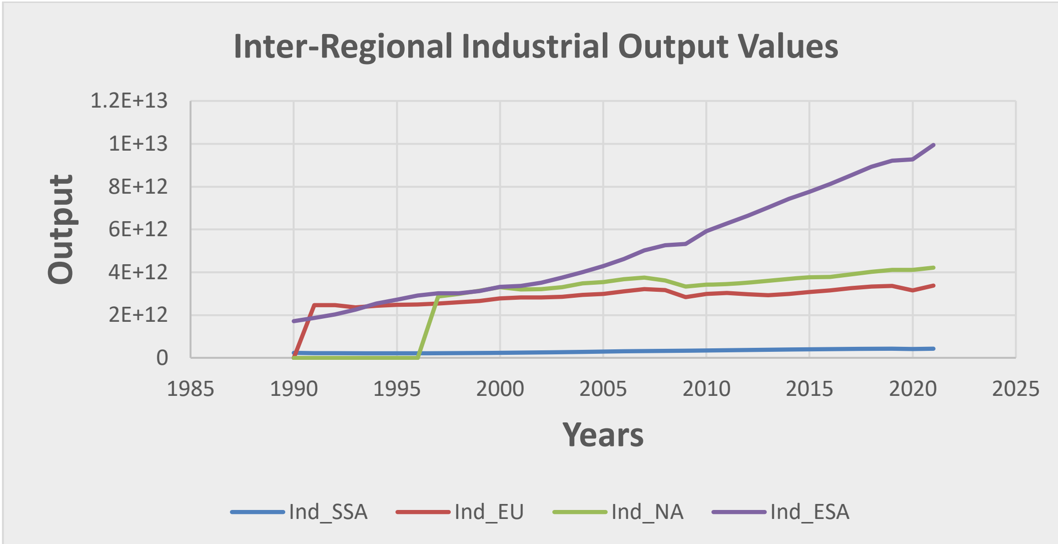


Figure 1.1: Inter-Regional Industrial Output Growth

Source: *World Development Index, (2022).*

In Figure 1.2, the background of the problems was discussed. Evidence from Figure 1.2 shows that industrial sector growth has struggled to rise substantially since the 1980s. Notably, concerns have been raised about why marginal increases in human capital skills and infrastructure development in SSA have not improved industrial output. On this premise, other emerging problems exist, which are pertinent to disclose in the cause of the study by providing a further way forward. SSA's inter-regional industrial sector growth performance was poor. Evidence on the curve showed HCD which is an indicator for human capital skill development, IFD represents infrastructural development, and IDO denotes industrial output growth (World Bank national accounts data, and OECD National Accounts data files; World Bank Global Electrification database & UNESCO Institute for Statistics, 2022). Theory suggests that an increase in human capital potential alongside an increase in infrastructure input leads to improved output growth (Lucas, 1988; Mankiw, Romer & Weil, 1992). However, emerging evidence from Figure 1.2 suggests otherwise, which is an implication for the problems in the study. Therefore, it is worth investigating why increases in human capital skills and infrastructure development do not cause industrial output growth in SSA. What might be responsible for the theoretical contraction for increased industrial output in line with increased human capital skills and infrastructure development? Notably, poor human capital skill development and infrastructure development might be responsible for the vast disconnection in Figure 1.2, resulting in low industrial output growth in SSA (Keji, 2021; Akinlo, 2022). Notably, the vertical axis explained the level of human capital skills, infrastructure and industrial output indicators in rate. In contrast, the horizontal axis captures the years.

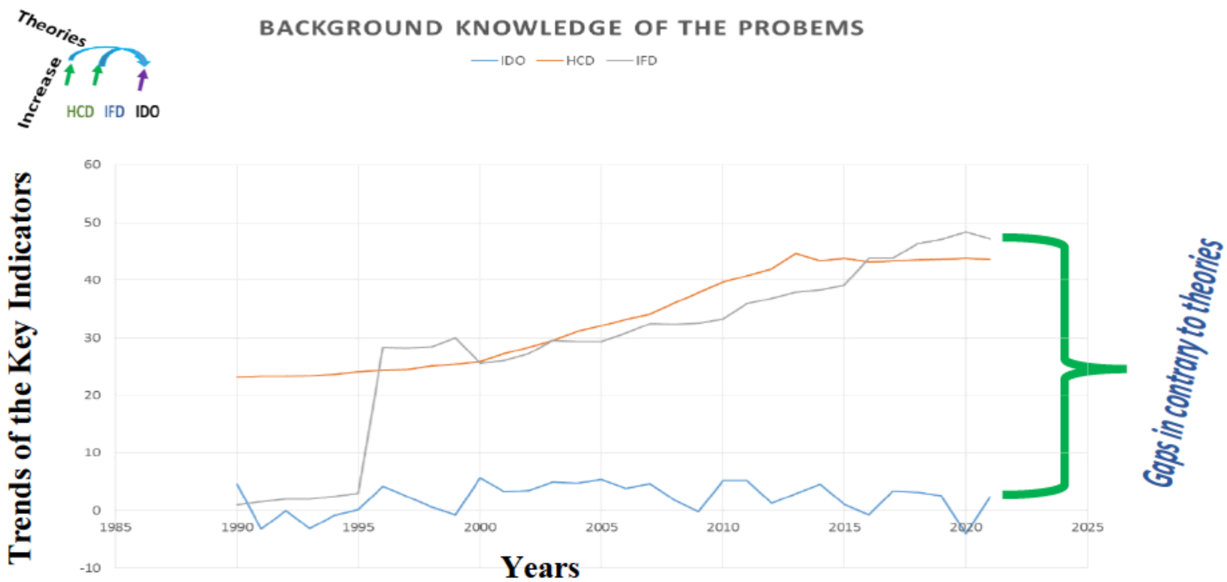


Figure 1.2: Background Knowledge of the Problems

Source: *World Development Index, (2022).*

Human capital and public infrastructural development are crucial to industrial sector growth. However, there is limited knowledge on how different factors determine industrial sector growth in small open economies across sub-Saharan Africa (SSA), where low technical skills, low productive output, infrastructural deficits, poor investment, and low technology, among other factors, constrain industrial sector growth (Mendes, Bertella, and Teixeira, 2014; Rewat Thamma-Apiroam, 2015; Obialor, 2017; Novignon & Lawanson, 2017, Mastercard Foundation, 2019; Akinlo, 2020; Keji, 2021; Du, Zhang & Han 2022). Secondly, how do the comparative effects of infrastructural development and human capital skill development affect industrial sector growth across sub-regional economic blocs in SSA? This addresses sub-regional specific effects regarding comparative advantage for industrial output growth within the economic blocs. Thirdly, to what extent did the asymmetric and threshold effects of human capital skills and infrastructure provide leverage for future policies towards industrial sector growth within the sub-regional blocs in SSA? This is one of the enormous gaps this study would fill, as studies on the asymmetric effect of human capital skills and infrastructure on industrial output growth in SSA are scanty. The above questions are pertinent because of the limited industrial sector growth in Sub-Saharan Africa due to low human capital skills and dilapidated infrastructure spread.

Furthermore, an improved human capital potential is crucial to industrial sector growth. The industrial sector entails well-skilled human resources (Kabongo & Mbonigaba, 2017). In Sub-Saharan Africa, limited human capital development could constrain industrial sector growth regarding unit input. However, there is a need to grow the industrial sector through the diffusion of knowledge, and human capital plays a crucial role in the industrial evolution agenda (Wonyra, 2018; Akinlo, 2020). For example, the policy question would be whether human capital skill is directly related to industrial output growth. How does human capital skills development via innovative skills catalyst industrial growth?

Africa has a massive human capital populace, and many reside in sub-Saharan Africa (Akinola & Mbonigaba, 2019). Despite this vast human capital deposited in SSA, sub-Saharan African governments have failed to develop innovative human capital capabilities in this populace, which has negatively affected industrial output growth (Torruam & Abur, 2014). Recent data from the Word Bank Development Index (2022) unveiled a sharp drop in industrial growth and a sharp fall in the value-added percentage to the SSA countries' production chain. This can be related to poor policymaking and implementation in the sub-Saharan African region, as most countries failed to implement UNESCO's recommendation of twenty-six per cent (26%) allocation from annual fiscal spending on advancing human capital skills development through education and infrastructural health facilities. Consequently, this would bridge the gaps in human capital skills like their counterparts from developed nations (Premium Times, 2017; Okumoko et al., 2018; Vanguard, 2021).

Infrastructural constraints are another issue that affects industrial sector growth (Babatunde, 2018; Keji & Keji, 2023). Infrastructures such as road networks and electricity, pre-determined by technology, are pertinent to industrial sectors' growth. The literature contends that infrastructure development is relevant to industrial sector growth (Orji, Worika & Umofia, 2017; Chinedu, Daniel, & Ezekwe, 2018; Du et al., 2022). Given the above, it is pragmatic to deduce that little or no government efforts were put in place and that there was no road map toward improving knowledge-based economies in SSA. Abdurraheem and Naim (2018) and Babatunde (2018) argued that infrastructure deficiency in the sub-region constrains human capital productivity and general productivity growth regarding output quality. Abdurraheem, Naim, and Babatunde (2018) posited that infrastructural deficits in SSA were attributed to poor technology presence and insufficient public funding from conventional sources via fiscal and multinational sources. Expanding production size through sustainable infrastructural spread across the sub-region is pertinent. Particularly in the case of sub-Saharan Africa, where resource constraints might be an issue, thinking at the margin is needed. Would investing more in human capital skills than infrastructure for industrial output growth within sub-regional economic blocs in sub-Saharan Africa be prudent or not?

Another vital issue that might affect industrial output growth in SSA is the business environment characterized by governance decisions regarding investment in human capital skills and infrastructure via public spending, business regulations, and ease of doing business, among others. Therefore, the trajectory needed to be implemented for informed investment decisions in human capital skills and infrastructure within the sub-regional economic blocs in SSA. Notably, the threshold trajectory and asymmetric effects would provide a necessary way forward towards addressing low industrial output growth (Shin et al., 2014; Kairo et al., 2017; Seo et al., 2019; Larcher, Kim & Kim, 2019; Du et al., 2023; Sama et al., 2023). The asymmetric and threshold effects of human capital skills and infrastructure on industrial output growth across individual sub-regional blocs are not well known, and findings from this study would provide the needed insights towards sustaining industrial output growth. For policy suggestions, it is worthwhile to investigate how asymmetric and threshold effects provide the basis for improving industrial output growth in SSA.

Another significant policy question is whether sub-Saharan African countries would set specific threshold points for investment in human capital and infrastructure, particularly at higher return to scale for industrial output growth. For example, infrastructures likely to be promoted via technological advancement for industrial output growth can be of different types, such as physical infrastructures such as road networks and transport, communication infrastructure, and other soft infrastructures like institutions that require sophisticated technology and high brainpower. Hence, there is a need to disclose how asymmetric and threshold effects predict endogenous skills that split through human capital along another critical indicator, like infrastructure, which can cause industrial output growth in SSA. Also, the threshold trajectory would show the basis for the complementarity effect of human capital skills and infrastructure on industrial output growth in SSA.

Consequently, over the years, it has been observed that the current state of industrial sector growth in the sub-Saharan African region contradicts the economic intuitions. This is because emerging evidence, particularly in Figure 1.2, contradicted what economic theories suggested due to its inability to align with the assumption of increased human capital skills and infrastructure indicators as the cause of increased industrial output growth. Evidence from the World Bank index suggested that SSA's human capital skills and infrastructure development were still low in innovation and creativity compared to other regions such as Europe, America, and Asia. The recent data from the World Bank via the World Development Index database showed that industrial sector growth does not align with the marginal increase in human capital skill development and infrastructural development in sub-Saharan Africa. Instead, it opened wide gaps that drew much attention and needed investigation. Also, with the recent projection by the IMF in 2021, which stated that SSA was the slowest recovery region when compared with East Asia and South Asia, among others from the recent pandemic, it is pertinent for the sub-region to drive its recovery through massive industrial output growth. The summarized and schematic illustration of the emerging problems regarding output growth in SSA are as follows:i) through the problem statement, and ii) through Schematic Configuration of the Problem Statement for Each of the Objectives, as explained in Figure 1.3.

1.3 STATEMENTS OF THE PROBLEM

The problems of this study are low human capital skills and poor infrastructural spread, resulting in low industrial output growth in Sub-Saharan Africa. This can be connected to the fact that the sub-region has the most minimal human capital skills development and dilapidated infrastructural spread that constraint industrial output growth (Babatunde, 2018; Keji, 2021; Du et al., 2023; World Bank Development Index, 2023). In theory, the quantum of human capital skills and infrastructure should drive industrial output growth. However, the contraction in the link between indicators for human capital skills, infrastructure and industrial output in SSA was quite alarming. And there is a need to investigate what might have caused this theoretical contraction despite concerted efforts by some countries in the sub-region towards improving production fortunes through human capital skills and infrastructure development. All those efforts have not yielded the desired results. Notably, SSA countries advocated for the persistent rise in school enrolment to bridge productive skill gaps as the primary source of human capital skills development. Also, efforts were focused on improving infrastructure through a persistent rise in annual outlay by SSA countries to address dilapidated infrastructural spread with less improvement in industrial output growth.

Moreover, much of the population is out of school, constraining skills advancement. The poor state of road networks and inadequate access to energy, among other critical infrastructure indicators, directly impede output growth. The consequent situations across the sub-regional blocs in SSA are low human capital skills and infrastructure development, hence slow industrial output growth. Experts have stressed that improving human capital skills and infrastructure will reverse this trend. Also, there were ongoing debates in the literature as to whether human capital skills and infrastructure engender industrial output growth and, consequently, industrial sector growth. Researchers such as Lucas (1988), Romer (1994), Mankiw (1995), Orji, Worika & Umofia (2017), Mastercard Foundation (2019), Keji (2021), Ndombi Ondze (2021), Amoah and Jehu-Appiah (2022) and Du et al., (2023) advocated for improved output growth through human capital skills and infrastructure development. Consequently, it is pertinent to investigate how low human capital skills and low infrastructure spread brought about slow industrial output growth in SSA. This is because relying on general findings from other developed regions across the globe might not be sufficient, which might not explain the current state of slow industrial sector growth in SSA.

Also, based on other evidence, the current situation is exacerbated by a lack of knowledge of modern human capital skills necessary to cope with the latest knowledge-based technology, as it fares better than general basic skills in promoting industrial output growth in SSA. The lack of knowledge on prioritising human capital skills and infrastructure development might compromise industrial sector growth. Furthermore, a lack of knowledge on structures of asymmetry and threshold might affect how investment decision is made by the authorities in SSA's sub-regional blocs towards human capital skill and infrastructural development within their respective sub-regional blocs, which later influence industrial output growth. This is because authorities in SSA have not been able to design policy frameworks at certain thresholds for industrial output growth. Therefore, the knowledge of how asymmetric and threshold effects influence industrial sector growth is germane. Finally, investment in human capital and infrastructure for industrial growth can be made marginally, starting with developing physical infrastructures that affect industrial sector growth in SSA.

In summary, productive skills and infrastructure needed for industrial development in Sub-Saharan Africa must be identified through quantitative analysis to see how the comparative effects of human capital skills and infrastructure affect industrial growth. The solution to the problem will also require how human capital skills, compared with infrastructural development, affect industrial sector growth. Also, how the asymmetric and threshold effects of human capital skill and infrastructure development influence industrial output growth for informed policy drafts across the economic blocs in SSA. In conclusion, the solution to the problem would require examining the empirical effects of various human capital skills and infrastructural development on industrial sector growth.

Notably, emerging problem statements revolving around the study's objectives were configured in Figure 1.3 to address the set goals in the study. This is to provide direct answers to the emerging questions from the problem statement. Consequently, policy-based solutions would be recommended to address each emerging question in the study. Then, the following schematic illustrations linked the configuration of the problem statement to address each of the background questions for possible answers, which was demonstrated thus;

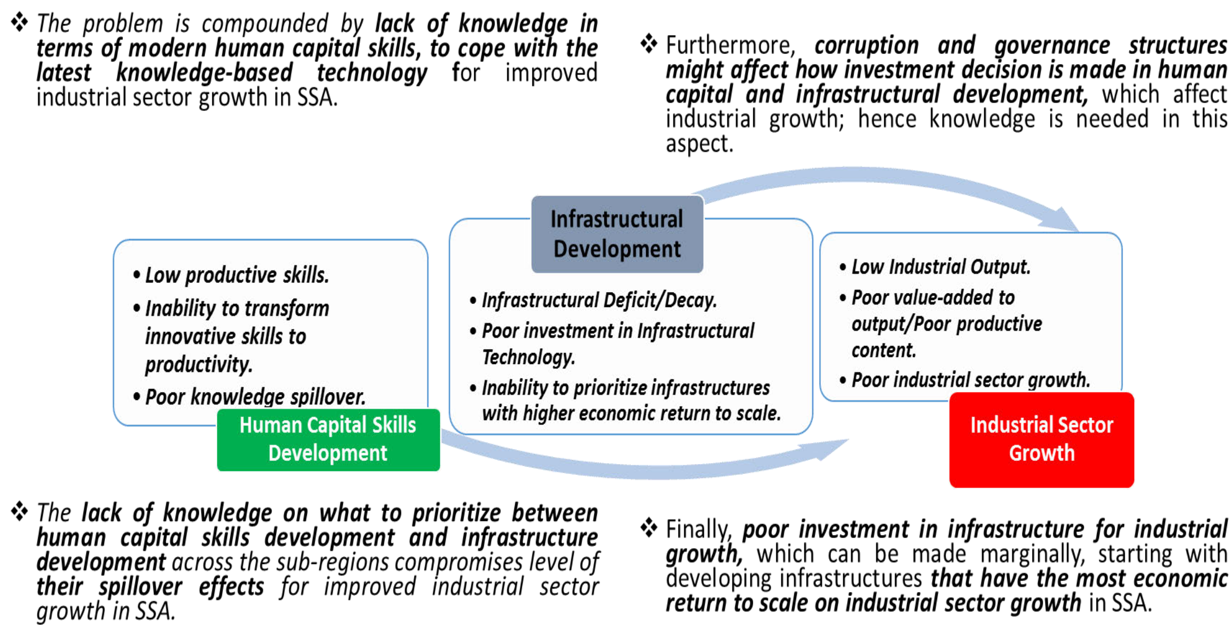


Figure 1.3: Schematic Configuration of the Problem Statement for Each of the Objectives

In summary, Figure 1.3 disclosed the link between the background problems and the concept of human capital skills and infrastructure development in SSA. The resultant effects of poor human capital skills and poor infratucture spread were demonstrated. This is to provide clear road map for industrial ouput growth in SSA.

1.4 RESEARCH QUESTIONS

The following questions emerge to address the pressing issues raised by the problem statements:

1. What factors determine industrial output growth in sub-Saharan Africa?
2. How do comparative effects of human capital skill and infrastructural development affect industrial output growth across sub-regional blocs in SSA?
3. What are the asymmetric and threshold effects of human capital skill and infrastructure development on the industrial output growth across sub-regional blocs in SSA?

1.5 OBJECTIVE OF THE STUDY

The broad objective of the study is to empirically investigate the effects of human capital and infrastructure development on industrial output growth in sub-Saharan Africa. While the specific objectives of the study are stated in the following order:

1. To investigate which factors determine industrial output growth in sub-Saharan Africa

2. To examine the comparative effects of human capital skill development and infrastructural development on industrial output growth across the sub-regional economic blocs in SSA.
3. To assess asymmetric and threshold effects of human capital skill development and infrastructural development on industrial output growth across the sub-regional economic blocs in SSA.

1.6 SIGNIFICANCE AND CONTRIBUTIONS OF THE STUDY

Industrial growth needs to provide employment and well-being in sub-Saharan Africa. Currently, the sub-region suffers from low industrial output growth. A study of this nature shall offer policy suggestions to promote industrial output growth in this part of the world. The impact of industrial growth would improve job opportunities, especially by revamping the presence of rampant primary sectors in SSA, such as mining and agriculture. This study solves the problem of poor employability skills possessed at post-secondary and tertiary levels across SSA. The study filled the vacuum of the sub-regional bloc regarding policy-specifics for addressing individual slow productive challenges across EAC ECCAS, ECOWAS, and SADC. Although previous studies such as Calderon, Cantu and Chuhan-Pole, (2018), Owusu-Manu, Jehuri, Edwards, Boateng and Asumadu (2019), Keji (2021) and Moneme, Okpara, Onuaja, Martin-Anthony (2024) attempted to address some of the important roles of infrastructure on output growth in a country case with a different focus from this study. None of the early studies accounted for the asymmetric and complementarity effects of human capital skills and infrastructure on industrial output growth across sub-regional economic blocs in SSA. This study provided insights into the dual effects (i.e. two regimes' effects based on asymmetric and complementarity effects) of human capital skills and infrastructure on industrial output growth across EAC ECCAS, ECOWAS, and SADC economic blocs in SSA. Notably, this study revealed the long-run dual regimes' effects of human capital skills and infrastructure on industrial output growth across the sub-regional economic blocs in SSA through school enrolment rate and access to energy for sub-region policy options. Accounting for the dual regime effects across economic blocs in SSA would improve productive synergy among the countries with similar production capabilities for industrial sector gtowth (Owusu-Manu et al., 2019; Moneme et al., 2024). Consequently, this study provided the need to redirect productive activities based on individual regional bloc in terms of economic cost advantage for industrial output growth, which emphasised the importance of the study.

Furthermore, the study addressed the poor spread of infrastructures with low human capital returns to scale across SSA. This study identified the sub-regional poor product identity regarding human capital skills and infrastructure spread. This was missing in the previous studies. Most importantly, a study on sub-regional economic blocs would provide more information to support policy frameworks across countries with similar product and economic identities, eventually facilitating the inter-country flow of industrial output growth. However, studies on a country-specific provide limited information for policy support.

Again, the study provided knowledge on how output growth can be achieved and sustained across different economic blocs concerning their specific human capital skills and infrastructural spread effects. Therefore, the study seeks to solve the emerging problems of industrial sector growth in SSA. Also, along the line, findings from this research shall address other issues associated with low industrial output growth, such as poverty, unemployment, under-employment, etc. A study that seeks to solve these problems is pertinent during this period of global resource belt-tightening prompted by pandemic shocks. The answers to the above challenges shall further contribute to crucial societal issues and the current policy debates.

At the SSA's level, the emerging answers to the questions raised in the study would redirect policy implementation by providing policy support for individual sub-regional economic blocs and the SSA region as a whole. This study paves the way for domestic policy concerning the actual cost of production at the economic bloc level. In addition, findings from this study would provide cutting-edge solutions to the challenges mentioned above and an indispensable guide for relevant agencies and policymakers in addressing future pressing issues. Once more, this research would serve as a future policy guide in decision-making for international agencies, international research institutions, like the International Monetary Fund, World Bank, African Development Bank, World Trade Organisation, SSA country's Apex banks, etc., and policymakers from all small open economies across the globe.

1.7 HYPOTHESES

The study tested the following hypotheses:

i. Human capital skill and infrastructure determinants do not affect industrial sector growth in sub-Saharan Africa. Short-run and long-run dynamic two-step system GMM were employed to test this hypothesis.

ii. Comparative effects of human capital skill development and infrastructural development do not affect industrial sector growth across the regional economic blocs in SSA. The Fixed Effect Least Square Dummy Variable (FE-LSDV), short-run and long-run dynamic two-step system GMM and robust diagnostics tests were employed to test this hypothesis.

iii. The asymmetric and threshold effects of Human capital skills and infrastructure do not affect industrial output growth. To test this hypothesis, panel threshold regression and non-linear Auto Regressive Distributed lag techniques were employed.

1.8 CONTRIBUTIONS OF THE STUDY

This study contributes knowledge in the following aspects, exclusively in line with the four sub-regional economic blocs in SSA and SSA's region:

(i) To the author's knowledge, there were no extant studies on the factor that determines industrial output growth, in which we provided evidence that industrial output (IDO) determinants vary across the sub-regions. We also offer empirical evidence beyond trend analysis to establish diverse effects of those determinants via a system GMM approach. Furthermore, the study systematically disaggregated the impacts of factors determining industrial output (IDO) through short-run and long-run two-step system GMM, a unique contribution to the extant literature.

(ii) Pertinent contributions on comparative effects were made via the joint and specific HCSD and INF effects analysis. We modelled for joint and specific impacts of HCSD and INF on the IDO models without mobbing up the models, as it was commonly mobbed up by previous scholars. This helps us to disaggregate factors influencing IDO to arrive at the divergent results in the literature on the individual effect of HCSD on IDO and INF effects on IDO at the sub-regional and individual country-specific levels. The regression analysis, FE-LSDV, and confirmatory two-step system GMM were used.

(iii) Furthermore, the study adopted disaggregated System Generalised Methods of Moment Condition (i.e. System GMM) to ascertain the short-run and the long-run effects of HCS and INF on IDO. This is a unique contribution to the extant empirical literature.

(iv) The study considered asymmetric and threshold effects of human capital skill and infrastructure. Therefore, non-linear panel model analysis was employed to ascertain the asymmetric impacts of HCS and INF on IDO across the sub-regional blocs. These were carried out to establish the effects of sub-regional specifics. Also, panel threshold regression was adopted to ascertain the production threshold for industrial output growth in SSA.

(v) The study incorporated AYS as the opportunity cost or time cost of skill acquisition and HOC as a factor for conducive learning and working conditions to propel productive output in the modelling. The study builds a model linking the two factors as predictors of HCSD and instruments of HCSD.

(vi) The AYS and HOC are valid instruments of industrial output growth. The study concludes that long-run HCSD and INF improvement can be achieved via better education and infrastructure road maps that should be supported by solid policy implementation at the sub-regional level and later be transmitted to the SSA region for equal spread of industrial sector growth in SSA.

1.9 SCOPE OF THE STUDY

The study focused on the nexus between human capital skill, infrastructure, and industrial sector growth in sub-Saharan Africa. This study covers the period from 1990 to 2022, thirty-three years. This period is predominantly relevant to the research and the history of the selected countries because it covers a period of deficit financing of long-term projects in human capital skills and infrastructure investment in some of the selected countries. Also, 1990 to 2022 is essential because SSA’s industrial history was characterized by reforms without significant progress in output growth. The study considered the two major shocks from the global meltdown in 2008 and the COVID-19 pandemic in 2019 that fall within the scope of the study.

1.10 STRUCTURE OF THE STUDY

Chapter one offers the background of the study, the problem statement, objectives, hypotheses, significance of the study, the study's contribution to the literature, the scope of the study, and its structure.

In chapter two, the author reviewed the relevant literature that encompasses the conceptual issues relating to this study and the theoretical framework. This literature in the study was presented as a reference point for the study's methodology.

Chapter three addresses the research methodology and covers relevant theoretical modelling and empirical models concerning each objective, data source, research design and techniques.

Chapter four addresses the factors determining industrial output growth across 40 SSA countries.

Chapter five compares diverse levels of human capital and infrastructural-tech effects on industrial output growth within and across sub-regional blocs in SSA.

Chapter six disclosed the asymmetric and threshold effects of human capital skills and infrastructure on industrial output growth across sub-regional blocs in SSA.

Note: Eeach of the chapters comprises three subsections. Section one summarises theoretical and empirical literature from SSA and outside the SSA region. The second section emphasises the methodology adopted to analyze the data for the study's objective. The third section deliberates on the empirical analysis and the implications for each objective.

Finally, Chapter seven presents the summary, conclusion, policy implications, and recommendations based on the findings.

1.11 SUMMARY OF CHAPTER ONE

This chapter addressed the background of the study, problems emanating from the background issues, and the problem statement. The sub-region outlook regarding industrial product identity is below par compared with other regions like East Asia, North America, and the Euro Area. This was connected with poor potential for value addition along with primitive production systems. This chapter presented the causes of slow industrialization, which paved the way for the research questions, objectives, and hypothesis. The scope and structure of the study were also highlighted in this chapter.

CHAPTER TWO

LITERATURE REVIEW

2.1 CONCEPTUAL FRAMEWORK

This study assessed how the endogenous nature of human capital skills and its endogenous effects, alongside infrastructural development, can catalyze industrial output growth in SSA. "As the new world economic order promotes knowledge-based economy. The study adopted the augmented endogenous theory through the re-modified AK, Lucas assumptions to support the analytical procedure in the first and second objectives, while Shin et al. (2014), Seo et al. (2019) and Larcher, Kim and Kim (2019) asymmetric and threshold frameworks underpinned the analysis carried out for the third objective. It is worth noting that this research was guided by theoretical, economic and econometrics intuitions, which were necessary conditions for model building. Models such as the *AK model*, *Arrow model*, *Uzawa-Lucas model*, *Romer model* and empirical analysis such as trend analysis, sub-sample regression analysis, system Genelised Methods of Moments (Sys-GMM), Fixed Effects Least Square Dummy Variable (FE-LSDV), Panel threshold regression, nonlinear Autoregressive Distributed Lags (NARDL) technique, among others post estimation tests were adopted in the study. For example, the robust standard error was adopted in GMM analysis against the usual downward bias standard error. Post-empirical checks such as Sargan/Hansen, first- and second-order autocorrelation tests, and stability diagnostics such as Wald, CUSUMS and Jarque Bera Normality tests were also used to validate our empirical results.

Human Capital Skills are pertinent to output growth. According to Wagner's 1876, as cited in Magazzino, Giolli, and Mele (2015), the nature of human capital skill, mainly through education, can be defined as a public good which promotes general productive growth. Also, acquired knowledge or human capital skills can be designed to expand machinery infrastructure for output growth (Ong, 2004). It is argued that knowledge can spread across the two pillars of economic principles to expand industrial output growth. Firstly, human capital skill can spread through small circuit units within production settings, often called micro-economic skill driven. Secondly, acquired human capital skills can be macro-economic driven to form aggregated skills that spread within and outside a small open economy for general productive growth. This level of knowledge spread is meant to improve product value addition and promote the production identity of that particular region or location (Ajayi, 2007; Lin, 2019).

Consequently, this narrative buttresses human capital theory, as posited by Becker (1964), who viewed sources of knowledge such as schooling and training as a stock of skill and know-how. Based on these narratives, the schematic configuration of productive knowledge/skills in a knowledge-based economy (KBE) is explained in Figure 4.5. The graph demonstrated how productive knowledge can be stocked for future transformation to sustain micro and macro-output growth.

Infrastructure is an important input of production. Magazzino, Giolli, and Mele (2015) argued that infrastructure was one of the significant sources of social needs that drive industrial output growth. The complementarity nature of human capital skills and infrastructure promotes output growth within micro and macro production circles. The implication is that knowledge plays a vital role in productive activities by transforming raw materials into consumable products using infrastructural tools such as energy, water, and others (Romer, 1988; Bokana &.Akinola, 2017; Lin, 2019). Ghahroudi et al. (2019) echoed this assertion by disaggregating knowledgeable skills into three different scopes: acquired knowledge, shared knowledge, and accountable knowledge, which are pertinent for balanced complementarity with infrastructural tools to achieve higher output growth.

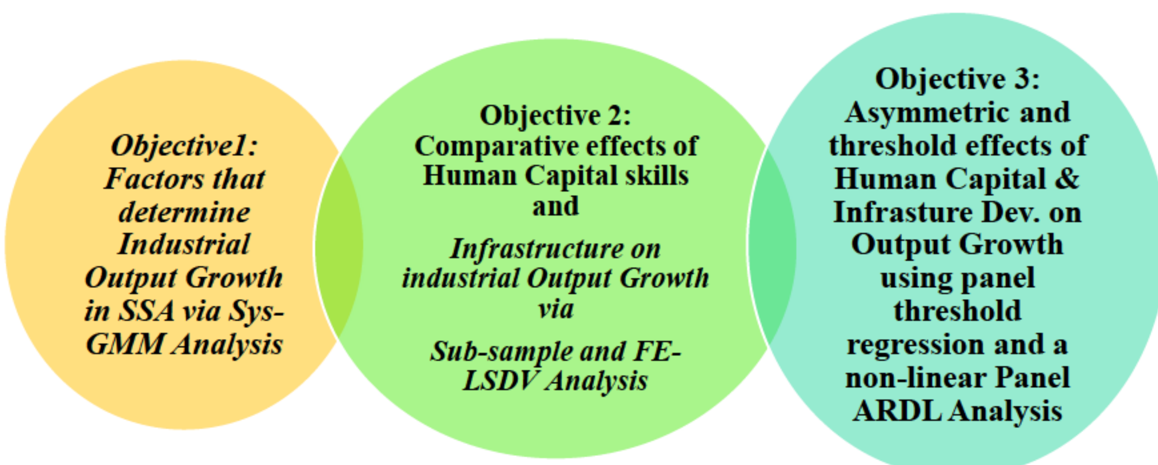


Figure 2.1: Linking Concepts with the Analysis of the Research Methods

The schematic illustration in Figure was aimed at disclosing the trajectory through which the concept for individual objectives in the study can be achieved. By revealing the trajectory of the concept through factors that determine industrial output growth through human capital skills and infrastructure. Also, Figure 2.1 shows how each of the objectives could be achieved with their respective econometric estimating techniques.

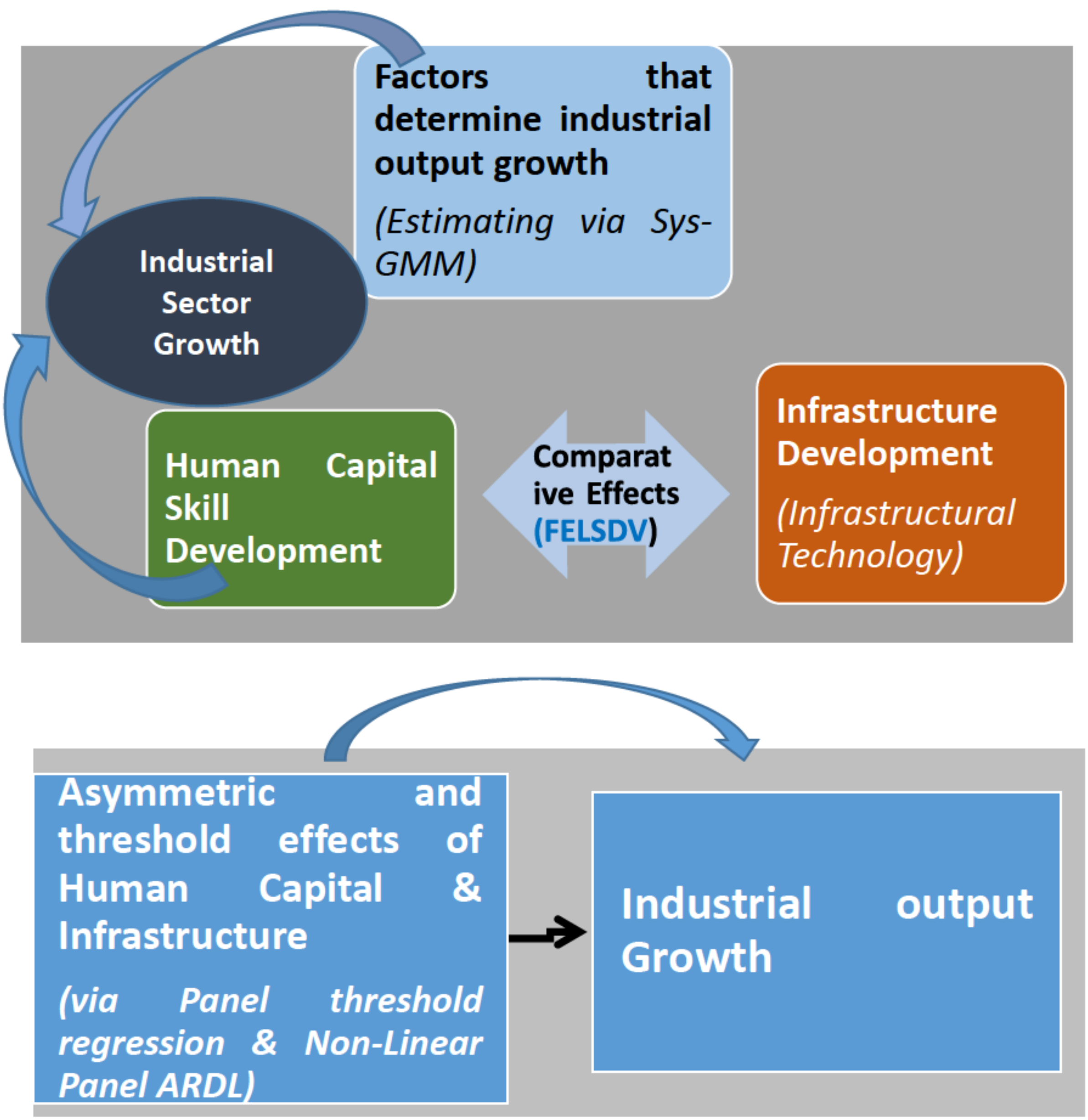


Figure 2.2: Schematic Configuration of the Conceptual Framework

Source: Researcher, (2023).

Figure 2.2 demonstrates how the concepts for the first objective flow through objectives two and three. This is to simplify the conceptual framework of the study. The history and structure of output growth have changed over the years via job creation and productivity. Hence, value-added skills to project sub-regional product identity are short in SSA.

Industrialization can be defined as the fast conversion of raw materials to industrial output within the same sector or across the sectorial composition. This includes the manufacturing sector, mining, service and utilities sectors. The roles of the industrial sector cannot be over-emphasised. Hence, it has been the mainstay of the real sector by driving structural transformation that later result in general economic growth and development (Oyakhilome, 2018). Industrialisation has been one of the significant sources of productive transformation and a solid path to fast-track a country's productive input-output growth (Kutu & Ngalawa, 2016). Therefore, the need to embrace industrialisation as a driver of structural transformation must be at the forefront of policy strategies and implementation for Sub-Saharan African countries.

Over the years, evolving trends of industrial output for the sub-region in line with functional and geographic division of production, application of advanced productive technologies for output growth were slow, and the SSA's downward output growth patterns were further compromised by climate change, and world pandemics, which characterized and shaped the general productive goods. Notably, the sub-Saharan African industrial output growth has experienced varied challenges, especially in recent times, where the output growth continues to decline (World Bank, 2022; Keji, 2023). The poor composition of human capital skills and the dilapidated infrastructure spread across the sub-region further complicated the downward growth. There were inadequate transportation networks, poor access to power, and policy inconsistency, among other challenges (Keji et al., 2024). Hence, improved output growth cannot be achieved by a system that depends almost entirely on primitive production methods with low human capital skills and dilapidated infrastructural spread.

A series of debates concerning industrial sector growth have generated much debate and speculation about the industry's prospects as a possible driver of employment creation, income growth and structural change in Sub-Saharan Africa (Ajayi, 2007; Lin, 2019).

Also, the trajectory of the share of industrial value-added to general output growth was alarming. It mainly depicts a flat or declining trend since the 1990s, and the recent year's scenarios have not seen any way of encouraging a reversal of this trend. This indicates a negative or modest labour productivity growth in manufacturing and partly explains the observed pace and nature of structural change in the region (Bokana & Akinola, 2017; Anyanwu, 2019). Notwithstanding the heterogeneity nature of industrial composition across countries in the region, it is pertinent as these would pave the way for robust estimating techniques.

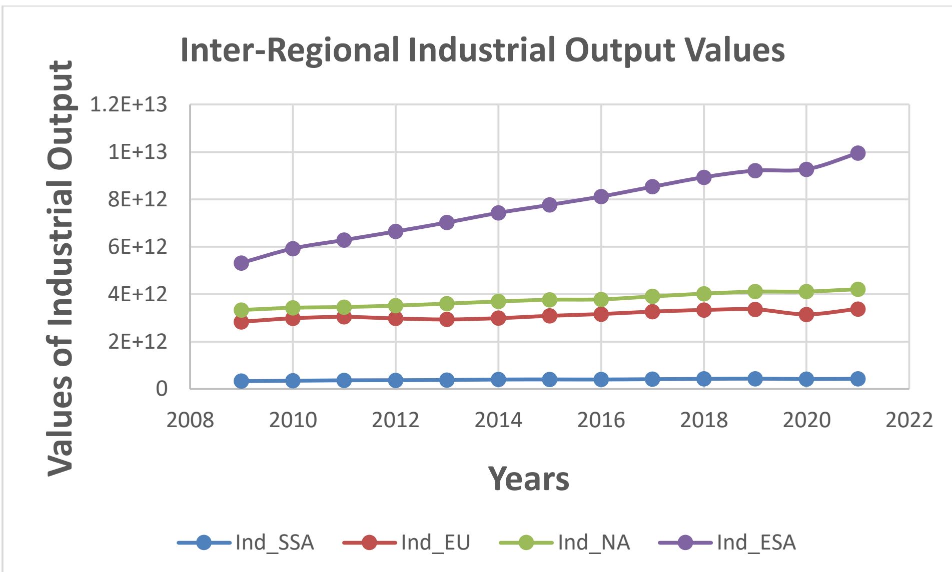


Figure 2.3: The Comparative Trends Analysis of Industrial Output across Regions

Source: Adapted from World Bank Development Index (2022).

Notably, in Figure 2.4, SSA denotes sub-Saharan Africa, EU signifies European Union, NA explains North America, and ESA represents Eastern Asia. It can be observed, among other regions, that industrial output growth, regarding values in Figure 2.4 for SSA, has continuously dropped close to negative values in recent years across the region. For example, the blue trend Figures representing SSA's industrial value-added indicator fell below zero per cent in 2020. It is worth noting that the SSA region recorded similar drops in industrial output growth in the years 1982, 1983, 1996, 1988, 1990, 1991, 1993, 1998, 2003, 2009 and 2020. The implication is that industrial output growth regarding value addition demonstrated slow growth in most periods under review. Hence, evidence showed low industrial output growth in SSA. This emerging problem was used to guide the scope of the study. Moreover, unravelling the necessary way forward towards industrial sector growth in SSA is pertinent.

2.1.1 Dynamics of Infrastructural Technology and Competitiveness

Importantly, in recent happenings in today's globalized industries, the skills for productive output prosperity have been subjected to infrastructural technological progress and human capital innovations that enhance the productivity of industrial factor output. The emerging new industrial competitiveness increasingly depends on infrastructural spread capabilities and innovation, and on the ability to apply new economically inclined infra-technologies in production, distribution and marketing, and to establish suitable connections with global firms in the form of mandating, production obligations, licensing, strategic alliances, etc. (Du et al., 2023). Therefore, international market competitiveness in many industries is rarely found in SSA. The region does not have a product identity like its counterparts from abroad. So, SSA needs resilient human capital skills and critical infrastructure supported by factor-input skills and innovations in its production process. In this regard, SSA and Africa must face the challenges by defining the level of infrastructure spread via technology that would enable enhanced industrial competencies and, hence, industrial competitiveness (Akinlo, 2020).

2.1.2 Dynamics of Human Capital Skills

Human capital is the impalpable or endogenous strengths and abilities that enhance productive performance to propel general output progress (Lucas, 1988; Mankiw, 1992; Romer, 1994). These abilities are inseparable from the person who possesses them. This considerable gap in industrial sector growth in SSA has not been fully explored. Therefore, the skills aspect of human capital is pertinent to output growth. The Nobel Prize winners at the University of Chicago during the late 1950s cum early 1960s were Becker and Schultz (1964), who principally posited for the development of the Human capital theory. Human capital and skills contribute differently to output growth at some point but may complement each other during the production process and development of the industrial sector (African Development Reports, 2011). Generally speaking, human capital skills can be sources of ideas, innovation and inventions (Lin, 2019; Keji, 2021).

These developed ideas can initiate new products and new content along the production chain. However, the opportunities to drive this potential are limited in SSA countries.

Furthermore, the skills required to show new product chains that can improve the industrial sector are pertinent to the study. Therefore, this study in chapters focuses on the knowledge and skills aspects of human capital, which include the time for acquisition, period of dissemination, and application to productive activities (Marchi, 2020). Short-term human capital skills in SSA undermine industrial output growth and industrial sector development (Kutu & Ngalawa, 2016; Keji, 2021). As a result, the region's economy mostly relies on activities dominated by low-skilled labour (such as agriculture or mining of natural resources), which impedes the demand for human capital skills, hence promoting low accumulation of human capital capabilities.

2.1.3 Threshold and Asymmetric Dynamics

The threshold in economic discipline and its application to economic phenomenon revolved around five major perceptions; integration, transformation, the irreversible, making the boundary and troublesome stage (Davies and Mangan 2007, 2008; Davies, 2012). The integration state explains the basic understanding of economic concepts. While the transformed state describes the ability to step forward in approaching economic phenomenon. The ireversible describes the inability to retract from some of the understanding of economic policies due to pressing economic conditions. Hence, certain boundaries are set inform of threshold for navigating economic policies and frameworks. Lastly, complexity emerges through troublesomeness and counterintuitiveness from external communities. Consequently, the dynamism of threshold and asymmetric effects are pertinent to operationalization of economic policies across SSA for industrial output growth.

Notably, threshold and asymmetric ideas concerning industrial output growth were designed in the study to address poor policy framework due to scarce knowledge in this regard. This is to adopt a more operationalised policy framework for industrial output growth across economic blocs in SSA. Meyer and Land (2003, 2006) posited that setting a certain threshold expands economically inclined ideas. Asymmetric and threshold are relevant to economic practices through different stages of economic change.

2.1.3.1 Concept and Application of Asymmetric and Threshold: The Conceptual Modification

The application of asymmetric and threshold to the study can be achieved through; i) type of conceptual variation, ii) type of application and incorporation and iii) examples through economics concepts. In number one (1), two (2) and three (3), the application of the concepts was discussed accordingly.

1. Basic economic policies: Understanding of newly embraced economic idea which transform understanding of everyday experience through integration of personal experience. Hence, capturing the discrepancies in respect to dual effects amongst price/cost; income/wealth (stocks/flows); nominal/real values; investment/saving. Real money balances, natural rate of unemployment (Davies & Mangan, 2007).

2. Discipline of asymmetric and threshold concepts: Understanding the applicability of related ideas and their effects on certain productive activities through integration and transformation of the knowledge acquired from theoretical perspective. Therefore, the dynamism of economic principles in achieving economic objectives at a certain threshold baseline emerged. For example, by exploring marginality and opportunity cost ideas (Davies, 2012).

3. Modelling the concepts of asymmetric and threshold: Understanding the empirical implications and its applicability to economic issues. Consequently, the dynamism and troublesomeness are conceived through rigorous economic concepts of comparative statics (equilibrium, ceteris paribus), elasticity, and short-run and long-run (Davies & Mangan, 2007).

<u>Narrowing the gaps of the subject matter:</u>

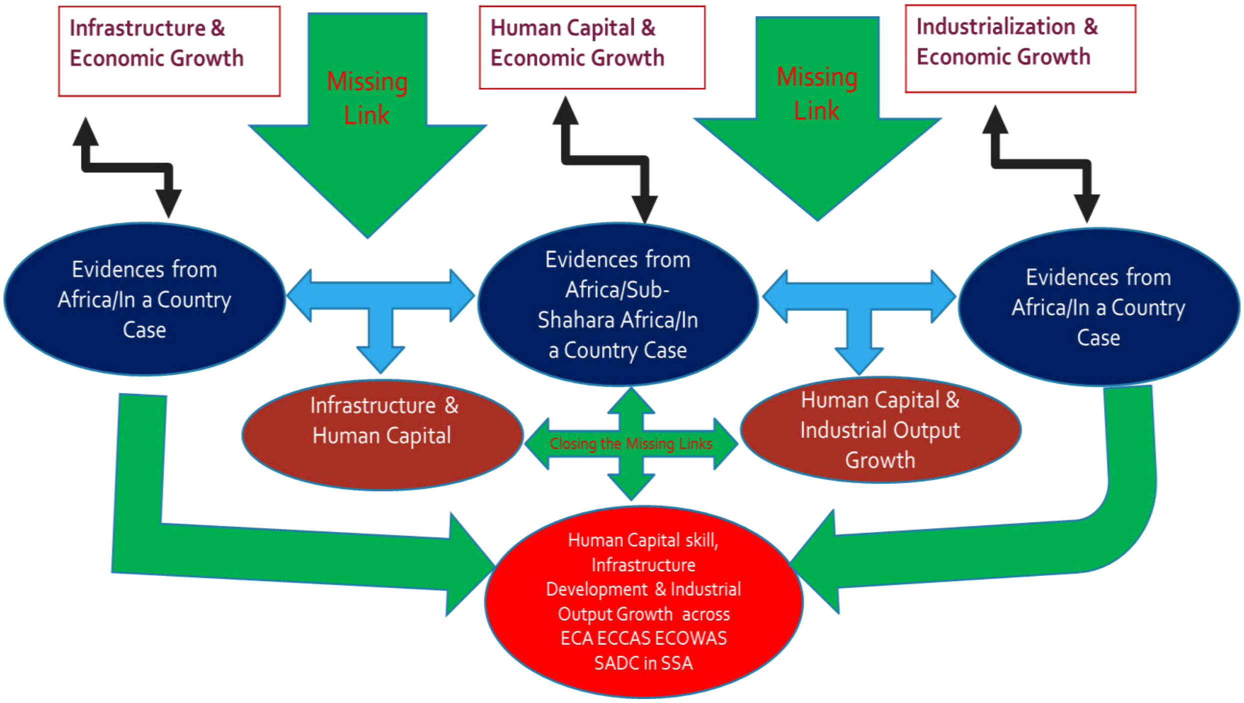


Figure. 2.4: **The Conceptual Gaps based on the project topic**

Source: Author's Review (2021).

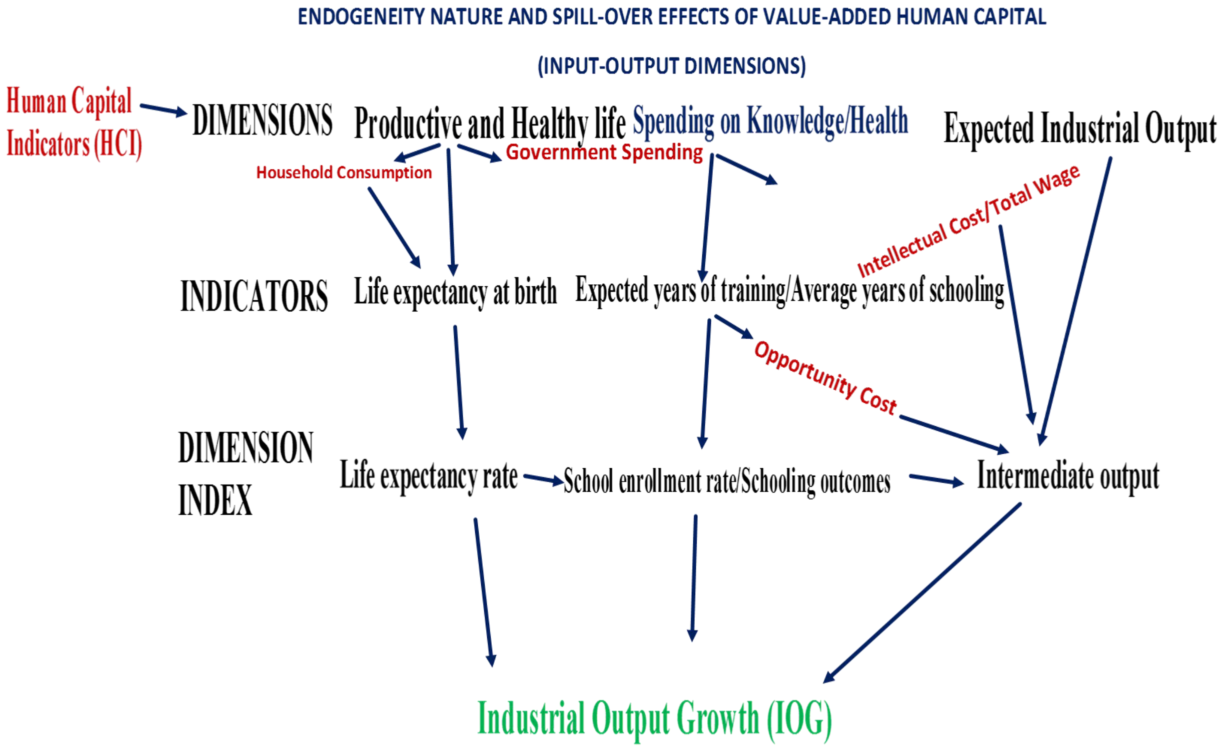


Figure. 2.5: **Comparative Gaps/ Dynamics Gaps**

Source: Adapted from Kairo et al. (2017).

The schematic illustrations in Figures 2.4 and 2.5 disclosed how this study filled conceptual gaps in the extant literature. The study structured its concepts from the generic perspectives to a specific point to address the problems related to individual sub-regional blocs in SSA. Notably, Figure 2.4 disclosed the unique nature of the concept in the study. The topic employed in the study was drawn from the missing links, making it a unique topic. The schematic illustrations further confirm the uniqueness of this study. Also, evidence in Figure 2.5 disclosed the dynamic nature of human capital skills and its comparative effects on industrial output growth. The evidence showed the background nature of knowledge transfer over time and the necessary conditions for actualizing knowledge spread, such as opportunity cost, household consumption, and government investment in knowledge and health. The input-output dimensions curves disclosed a series of factors influencing industrial output growth performance in SSA.

2.2 THEORETICAL REVIEW

Numerous concepts explain the link between human capital, infrastructure development, and output growth. Theories are likened to pillars upon which research foundations are built. They are authorities upon which expectations of research work are translated into an acceptable argument. They explain in-depth paradigms from expectation to research realities. Theory allows a researcher to name what was observed and explain the relationship among concepts. It allows the researcher to explain what he sees and to figure out how to bring about change through his findings. Theory is a tool that allows a researcher to identify a researchable problem, and it is a mediating means for altering the situation. Consequently, the following theories guided the investigations expected in this study.

The major motive of the study was based on the premise that human capital possessed skills along with the composition of infrastructure, which can cause industrial output growth in SSA. This is because endogenous growth theorists posited the direct effects of human capital and infrastructure effects on industrial sector growth. Timely investigation around this assumption among the economic blocs in SSA is pertinent due to the scarce nature of this kind of research from previous studies, and it is essential to ascertain which of the key independent variables of measurement needed to be prioritised for efficient resource allocation in one hand and competitive advantage in the other hand. Notwithstanding, tenets of the theories that explain the importance of improved human capital skills and infrastructural techs for productive growth are hereby reviewed.

2.3 THE LITERATURE REVIEW AS APPLIED TO THE STUDY

Economic literature proves that factor inputs such as knowledge and physical capital can be transmitted out of the abundant stock of wealth through appropriate complementarity processes to influence general output growth. For example, human capital can be defined as knowledge, skills, and experiences accumulated over time, while physical capital can be described as a set of machines and machinery injected into the production process. Notably, in a knowledge-based economy (KBE), knowledge can be designed to expand along machinery infrastructure for output growth. It is argued that knowledge can spread across the two pillars of economic principles, thus: 1) Micro knowledge driving. This is knowledge within the micro-management settings to strategically overcome other competing firms within the same business chain or industry. 2) Macro knowledge driving. It explains how aggregated knowledge from a knowledge-based economy can outsmart other internationally competitive productions by improving product content and adding value to productive output. Consequently, this narrative buttresses Gary S. Becker's 1964 human capital theory that viewed sources of knowledge such as schooling and training as a stock of skill and know-how. Based on these narratives, the schematic configuration of productive knowledge/skills in a knowledge-based economy (KBE) explains how productive knowledge can be stocked for future transformation to sustain micro and macro-output growth.

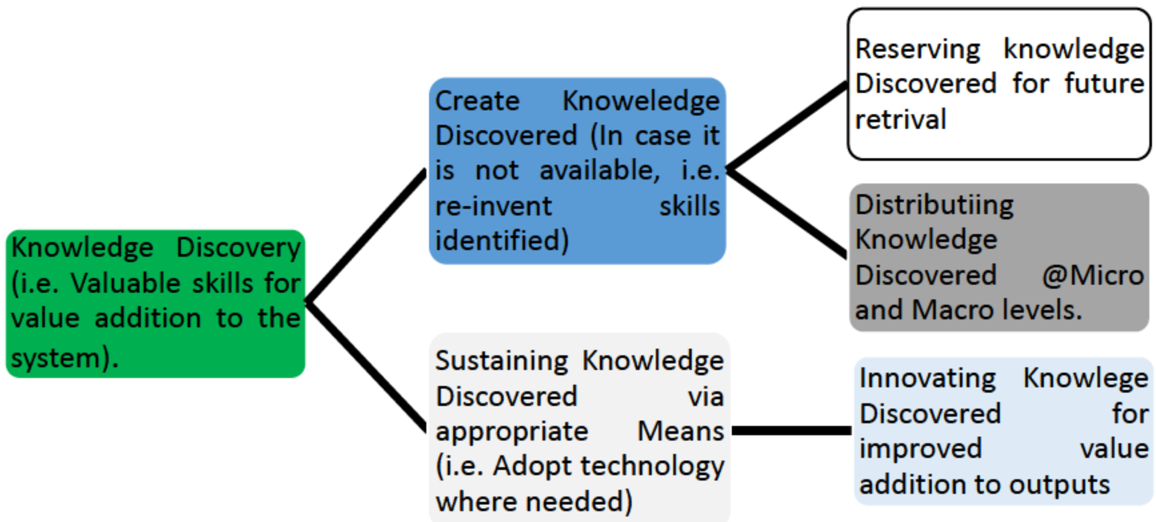


Figure 2.6: Schematic Configuration of Knowledge/Skills in a Knowledge-Based Economy (KBE) for Productivity Growth.

Source: Adapted from Johnson Ong (2004).

It is worth noting that the significant purpose of the study is based on the evidence of how endogenous factors determine industrial output growth in SSA. This is because endogenous growth theories posited a direct effect of endogenous variables, such as human capital skill development, on output growth. A timely investigation of this assumption in the case of SSA is pertinent. Notwithstanding, tenets of the theories that explain the relevance of human capital skill to industrial output growth are reviewed.

Also, economic literature provides significant evidence that governance can improve economic factor inputs such as human capital and physical capital for productivity growth. The endogenous growth theory contends that an internal factor causes output growth within the production system (Romer, 1986, 1994; Lucas, 1988; Lucas, 1988; Mankiw, 1992; Thabane & Lebina, 2016; Durmaz & Pabuçcu, 2018; Zhang, 2018). The rudiment of endogenous theory assumption was based on the fact that both human capital development and technical progress can cause output growth in an enabling environment where complementarity roles of internal factor inputs are sustained and well actualized. Hence, a nation's output growth status is measured by the extent to which input factors of production, like human capital and infrastructure, are well combined and utilised.

Notably, the primary investigation in the study is how infrastructural-technology development and human capital skill development endogenously contribute to industrial sector growth across the sub-regional economies in SSA. This notion arises from the endogenous growth theory underpinning this study, which echoed the well-actualised essential roles of infrastructure and human capital skills as causal of productive growth, all things being equal. Also, investigating this theory in the case of SSA is necessary, based on the scarce study of this nature. Remarkably, the core theory that addresses the roles of human capital skills and infrastructure concerning output growth was well discussed in chapter two.

Consequently, theoretical models of human-physical capital rested on the assumption that the embodiment of knowledge and skills acquisition in human capital and general technical progress, such as ICT and road networks, among others, are public goods that dictate productive growth. It is worth noting that, if not none, previous empirical findings were either mixed or scarce on this aspect of research. Notably, the diverse scholarly predictions emerging from SSA have raised policy questions on the need to ascertain the non-linear impact of human capital skills and infrastructural facilities on industrial output growth. Also, this study fills a gap in the literature by carrying out context-relevant policy for the sub-region specifics within SSA and individual countries in SSA. On this premise, related studies were reviewed.

2.3.1 The Neoclassical Growth Theory

Neoclassical theory emphasizes that economic output is based on savings, technical progress, and population growth, all equal things (Nicolaides, 1988). This theory states that output growth can be achieved through either of the three factors or more of the factor inputs, such as increased level of labour unit input and population growth (i.e. rise in quality and quantity of labour), rise in capital investment (i.e. investment in physical capital inputs), and technological advancement (i.e. raise in inventions and innovations) (Solow, 1956; Nicolaides, 1988). That is, per capita growth rate differences persist when the level of technical progress differs across nations (Ebong et al., 2016). However, Solow and Swan (1956) tried to improve the neoclassical model through the addition of other relevant growth-driven variables such as investment, education and technology, as well as identifying some important transmission channels of these variables through economic theory and their links between technological progress, capital inputs, and economic output growth. Still, the model seems lopsided as it could not account for endogenous factors that form part of the capital inputs as an active ingredient of industrial output growth, though it paves the way for us to achieve this study's objectives. For example, the neoclassical growth model, especially the Cobb–Douglas model, as postulated by Solow-Swan (1956), is an economic model of a long-run unit of output growth set within the neoclassical ideas. This model explains exogenous long-run output growth through capital accumulation, labour or population growth and technological progress as sources of productivity growth. At its core is a neoclassical (aggregate) production function, often specified to be of Cobb–Douglas type, which enables the model "to make contact with microeconomics decisions on productivity (Akinola & Mboniga, 2019). This model allows for the technologically advanced aspect of productivity associated with technological transfers such as infrastructural technology. Typically, the Cobb-Douglas model was independently designed by Robert Solow and Trevor Swan in 1956, and it superseded the Keynesian and Harrod–Domar models regarding measuring output growth in this study.

Mathematically speaking, the Cobb-Douglas model is a nonlinear system consisting of a single ordinary differential equation that models the evolution of the per capita stock of capital mostly through internal investments. Under this scenario, the implication of capital stocks on output growth can be seen through its effect on both domestic and foreign investments, which are eventually used as investments in an open model (Ebekozien, Ugochukwu, & Okoye, 2015; Bokana & Akinola, 2017; Akinola & Mbonigaba, 2019).

Consequently, in Solow's model, other things being equal, such as investment via capital accumulation and population growth, are important causes of output growth. "Higher investment rates lead to more capital per worker accumulation, especially when technology is being transferred between the countries." Without technological change and innovation, an increase in capital per worker would not be matched by a proportional output increase because of diminishing returns. Hence, capital deepening through technology transfer from FDI would increase the return rate on output.

Also, there are several theories that link human capital skills and infrastructure development with industrial output growth. Some economic models have viewed human capital as a source of output growth (Lucas, 1988; Rebelo, 1991 & Mankiw, Romer, and Weil, 1992). While some other models see human capital and infrastructure as improving social needs (Wagner, 1876; Keynes, 1930, as cited in Udo & Efiong, 2014 & Magazzino, Giolli and Mele, 2015). The leading models are the endogenous growth model, Wagner's law (model), and the Keynesian model.

2.3.2 The Endogenous Growth Theory

The endogenous growth theory is the leading theory underpinning this study. This theory fits into the objectives of this study as it addresses internal factors such as industrial output growth through continuous government investment in human capital development and infrastructural advancement. Increased productive capacity is determined by increased infrastructure knowledge-based development (Romer, 1994). Endogenous growth theory is built on internal factors through continuous increases in inventions, human capital skills, and knowledge to enhance productivity levels that contribute to all-encompassing output growth. The theory endogenously supports factors that lead to industrial output growth through returns from human capital and innovations, which promote a knowledge-based economy (Rebelo, 1991). The endogenous theory was designed to address the limitations of exogenous growth theory that could not accurately account for changes in individual productive capacity and technologically improved infrastructural progress. As a result, the endogenous growth theory focuses on the merits of technological advancement due to the comparative effects of accumulated knowledge acquired by human capital that spread through infrastructure development. The complementarity effects of human capital potentials and infrastructure spur general output growth (Rebelo, 1991; Mankiw, Romer, & Weil, 1992). Because human capital returns determine the change in productivity levels, which also depends on infrastructural technological progress through government spending on public goods (Wagner, 1876; Keynes, 1930, as cited in Udo & Efiong, 2014; Mankiw, Romer, & Weil 1992). This complementarity effect portrays the endogenous nature of our key variables that the exogenous neoclassical theory cannot extensively address.

2.3.3 The Wagner's Law of Public Goods as Social Welfare

In response to the nature of human capital skill via education as a public good and infrastructure as the sources of social needs. According to Adolph Wagner's 1876, as cited in Magazzino, Giolli, and Mele (2015), there were fundamental reasons for government involvement in general output growth. One of the reasons for this is to expand industrial growth through investment in public goods like infrastructure, education, etc. The government cannot increase industrial progress through general spending but through targeted spending on factors promoting industrial growth. Wagner argued that complexity in society makes the increase in government expenditure inevitable across various sectors to facilitate efficiency in education output (labour skills) as the division of labour arises (Udo & Efiong, 2014), necessitated by social change for output growth sustainability. Overall, investment targets on infrastructural goods are positively linked with general output growth (Keji & Efuntade, 2020). Meanwhile, Grossman's model (1972) used health production as the output of socioeconomic inputs such as education, nutrition, income, and employment status, which form individual health stocks at the macroeconomic level, another cause of industrial output growth.

2.3.4 The Keynesian Argument on Output Growth Theory

Keynesian model explains the vital roles of aggregate improvement in production in an economy. Keynes worked on diverse views regarding the connection between infrastructure and output growth. On the one hand, the increasing infrastructural outlay is believed to bring about economic progress. On the other hand, the rising public investment in infrastructure can depict growth due to crowding out effects on vital economic investment. Udo and Efiong (2014) agree with Keynes' first assertion that public investment improves output growth. However, Nurudeen and Usman (2010) agree with Keynes's second assertion that continuous government efforts through social investment can disrupt output growth because the need to raise public spending may prompt higher taxes or borrowings. Hence, Keynes's model seems to be less practicable for various economic situations in different SSA economies. Still, it instead gives economists (us) many choices to explain possible economic phenomena whenever there is a disruption in employment and output growth in the long term. Therefore, to explain the third specific objective of this study. The knowledge from the Keynesian framework provides us with many choices.

2.3.5 The Proponents of the Endogenous Output Growth Theory

As the pioneer and advocate of endogenous growth theory, Romer came up with internal perspectives for achieving output growth. His works of 1983 and 1986 were based on ideas and knowledge as the essential tools of output growth. Similarly, Lucas argued that individual stock of knowledge raises productivity growth through more investment in human capital. In his 1988 work, Lucas suggested that decentralized models are under-utilised since the individual cannot transfer whole gains of accumulated knowledge to the larger economy. Therefore, there is a need to subsidy this stock of knowledge to correct externalities that would produce socially optimal units of human capital. By the 1990s, other followers came up with different arguments; Rebelo (1991) opined that perpetual growth is achieved through combinations of endogenous inputs, which can be stocked without diminishing returns.

Meanwhile, Mankiw refutes Lucas and Rebelo's claims that human capital can be infinitely amassed because the human life span is finite and later tries to provide more insights into the human capital model. He argued that human capital could not be accrued without definite and weakening returns as this was unrealistic to an individual. Knowledge cannot be generalised because the optimization problem replicates an individual's yield, while any individual adds only a slight share of the entire knowledge. Therefore, Mankiw called for understanding endogenous growth's fundamental model(s). Given this, Mankiw, Romer, and Weil (1992) developed "the augmented Solow model." This model is an improvement from previously built by Solow and Swan (1956) - $Y = AK^{\alpha}L^{\beta} \ldots \ldots \ldots (1)$, which failed to explicitly and endogenously incorporate human capital skills. Even though Solow and Swan's (1956) neoclassical theory stands as the innovator in this aspect to serve as the basis for the rise in several endogenous models that were established to integrate the accumulation of human capital skills in the industrial output growth process.

The basic tenets of the endogenous output growth model are explained thus: The endogenous growth model rests on the following tenets thus: Firstly, it is believed that output growth is caused by internal factor inputs rather than external ones. Secondly, industrial output or productivity increase can be directly aligned to improve innovations and investment in human capital via research and development funds (R&D) as source output growth. Thirdly, increasing return to scale is believed to be achieved by developing human capital through infrastructure (physical capital), education, and health. Lastly, public policy promotes entrepreneurship as a source of new investment and innovations. The comparative effect of innovations via infrastructure and acquired skills would generate high human capital returns, especially in knowledge-based industries (Romer, 1986). Hence, these endogenous views contrast with neoclassical views.

This literature extensively demonstrates the comparative effects of human capital skill development and infrastructural-tech development on industrial output growth. The pioneer and advocate of endogenous growth theory, Romer (1983), came up with internal perspectives for achieving output growth. Romer (1983) and (1986) advocated for ideas and knowledge as the essential tools of output growth. Similarly, Lucas (1988) argued that individual stock of knowledge raises production growth through more investment in human capital. In his 1988 work, Lucas suggested that decentralized models are under-utilised since the individual cannot transfer whole gains of accumulated knowledge to the larger economy. Therefore, there is a need to subsidize this stock of knowledge with physical capital, such as infrastructure, to correct externalities that would produce socially optimal units of human capital for output growth. This assertion further reaffirms the importance of factor inputs' complementarity during production. By the 1990s, other followers came up with different arguments; Rebelo (1991) opined that perpetual growth is achieved through combinations of endogenous inputs via human and physical capital, which can be stocked without diminishing returns. To balance the combined effects of human capital skill and physical capital, such as infrastructure, as factor inputs of production, Rebelo (1991), Mankiw, Romer, and Weil (1992), and Lucas (1988) supported the augmented endogenous model, as against the neoclassical model previously built by Solow and Swan (1956).

Consequently, this study examined the comparative effects of human capital and physical capital as factor inputs for industrial output growth among economic blocs in SSA. A study of this nature tries to come up with a different perspective in assessing the specific effects of human capital skill and infrastructural tech on industrial output growth, which is different from the early studies. Most of the previous works were either concentrated on the broad aspect of measurement for human capital development without much concentration on the skill aspect of human capital that is directly pertinent to industrial output growth (e.g., Eigbiremolen & Anaduaka, 2014; Bennett, Anyanwu & Kalu, 2015; Friedrichs, Keeton & Rogan, 2021; Keji, 2021). Also, most early works duel much on broad effects of infrastructure that are not closely endogenous to industrial output growth, which is on general economic growth in a country case study (e.g., Fedderke, & Bogetić, Željko 2006; Du et al., 2022). At the same time, few related studies are entirely different regarding scope and focus from this study.

Interestingly, based on the review of the existing pieces of literature, it is glaring that work of this nature, which attempts to narrow down the aspect of human capital and infrastructure through sub-regional blocs comparative effects on industrial output growth, appears to be scanty, and there are still ongoing debates on which of the key factor-input should be prioritised for industrial sector growth. Hence, findings from this study would contribute to the literature by identifying the extent and importance of comparative effects of human capital skills and infrastructure tech development among intra-regional economic blocs on industrial sector growth. The following section introduces the schematic illustrations of the gaps to be filled in the study, using the trend analysis, empirical findings, and justifications for the methodology of analysis to actualize our second objective.

2.3.6 The Criticism of the Neoclassical Growth Theory

The criticism of the neoclassical growth theory is explained thus: The first spot of criticism of neoclassical growth theory is that the theory cannot be validated. Critics opined that the neoclassical economists' assumptions and tenets fail to explain the necessary basic growth behaviour (Nicolaides, 1988). Also, the model fails to address the substantial mystery behind output growth paths. Interestingly, this criticism assists the neoclassical school in looking inwardly and propelling the endogenous growth theory on which this study is built.

Moreover, there was a joint failure from the endogenous model protagonists to describe conditional convergence in the empirical literature. Also, the theory has not been able to justify the predicted diminishing to capital. Also, the critics faulted the assumption of using one production function to represent the complexity of the society where the production process cannot be predicted in a single model.

2.3.7 Other Evolving Models and their Applicability to the Study

In the past, theories on human capital were attributed to economic gains, which are entirely different from sociological perspectives. Socio-economic factors such as a conducive work environment that enhances returns from education form the new trajectory in the study of the endogenous growth model (Perepelkin, Perepelkina, & Morozova, 2016). These evolving models of human capital and output growth are discussed as follows:

2.3.7.1 Arrow Model

Explains the change in economic activities caused by improved human capital due to changes in innovations and technology. This model shows how self-practising promotes increased productivity via sophisticated human capital. The arrow model is a "learning by doing" model and can also be called the AK model. Notably, this model is relevant for achieving a second specific objective. The Arrow Model: Arrow model explains the change in economic activities caused by improved human capital due to changes in innovations and infrastructural technology. An implication for the first and second objectives (Romer, 1983; 1986).

2.3.7.2 Uzawa-Lucas Model

This model suggests that human capital accumulation can accomplish long-term output growth. The model argues that educational attainment should be used as the source of human capital. Also, the Uzawa-Lucas Model submitted that human and physical capital are to be used to expand productive output, as the human-physical capital ratio measures the total capital employed in an economy. This model is relevant to the second specific objective of the study. The Uzawa-Lucas: Uzawa-Lucas Model submitted that both human and physical capital such as infrastructure are to be used to expand productive output, as the human-physical capital ratio measures the total capital employed in productivity(Piabuo & Tieguhong, 2017; Olaniyan & Okemakinde, 2008). This model was particularly relevant to the second objective in the study.

2.3.7.3 Romer Model

This model considers improved human capital and technology as endogenous inputs, leading to output growth. It is assumed that knowledge-based ideas are vital ingredients of economic progress; integrating the existing knowledge and human capital can lead to innovative ideas needed to increase the production of goods and services (Romer, 1983; 1986). Therefore, given the above, this study intends to achieve the first, second and third specific objectives by building on endogenous growth theory from Lucas, Mankiw, Romer, Rebelo, and Weil models and a few Keynes's perspectives and Wagner's law. This model considered an improvement in human capital and infrastructural technology as endogenous inputs, leading to output growth. The AK model: Model of "learning by doing" the AK model (i.e. Labour units per production coincided innovations via population size) (Romer, 1983; 1986). This was an implication for the first objective.

2.3.7.4 The Convergence Theory

This model explains that the growth in human capital development in developing economies should quickly catch up with developed countries' none-speeding human capital growth. Ultimately, the human capital developments would converge at the equilibrium; hence, they move on together. This is an implication for this study since most of the countries under focus are developing countries where their human capital and infrastructure growth are lagging. This model explains the need for growth in human capital development in developing economies like SSA to quickly catch up with the none-speeding human capital growth of developed countries, which was an implications for the study.

2.3.7.5 Fiscal Illusion Theory Arguments

Fiscal illusion theory was invented from the work of Puviani (1903) (as cited in Mourao, 2008) and a contribution from Buchanan (1967). Fiscal illusion is about the mix-up of fiscal parameters. The crux of this concept is to uncover the detail that, at times, the business environment comes up with programs to put up needless projects that disrupt industrial output growth. Interestingly, this concept is pertinent to this study because it addressed how policymakers diverted infrastructural projects that would have automatically converted to expected industrial output growth, as established by the assumptions of illusion theory. Again, Oates (1985) contends that misunderstanding fiscal constraints could substantially alter economic varieties. The finding was explained in line with this theory as an avenue to disclose the path of fiscal illusion in the cost and benefits investigation regarding government expenditure on social amenities towards achieving the needed industrial growth. Fiscal illusion is about the mix-up of fiscal parameters. The crux of this concept is to uncover the detail that, at times the government comes up with programs to put up needless expenditure.

2.3.7.6 Opportunity Cost Theory

This theory argues that accumulating higher education human capital provides counter-cyclical realities. According to this theory, higher human capital skills acquired become relatively more productive during a downturn when economic conditions are disparaging. This is because the corresponding opportunity cost regarding skilled labour within the market setting is likely forgone due to the relatively smaller size during the recession period (Saint Paul, 1993).

2.4 SUMMARY OF THE THEORETICAL LITERATURE AS APPLIED TO THE STUDY

2.4.1 The Protagonists of Neoclassical Growth Theory

This literature widely attests to the physical capital impact on output growth. The neoclassical model stresses that economic output is built on capital accumulation and technical advancement, all things being equal (Nicolaides, 1988; Rumanzi et al., 2021). Neoclassicists posited that output growth could be attained via any of the two factors or other inputs, like an increase in a unit of capital-input and technology growth (i.e., a rise in quality of both labour and physical capital like infrastructure) and a rise in capital-investment (i.e., physical capital investment as an input), and technological progression (i.e., increasing in discoveries and innovations) (Solow, 1956; Nicolaides, 1988). That is, per-capita growth rate variances continue when the rate of technical advancement varies across countries (Ebong et al., 2016). Consequently, Solow and Swan (1956) improved the neoclassical framework via mathematical modelling to show the link between technological growth, physical capital, and economic output growth. Therefore, the Solow and Swan (1956) model explained the exogenous aspect of indicators comprising the capital inputs as a key element of industrial output growth, allowing us to attain our objectives in the study. The essential roles of capital accumulation as a critical factor input of output growth as modelled by Solow and Swan (1956) aligning with the version of the Cobb-Douglas function is relevant in this study.

Because of this, theoretical modelling for capital input, such as infrastructure, is assumed to influence output growth directly. However, empirical works in SSA are primarily inconsistent with this theoretical assumption. Also, there is insufficient evidence to attest to this theoretical groundwork regarding the infrastructural indicators influencing industrial output growth via disaggregated system GMM. For instance, the contrary deductions from studies like Bennett, Anyanwu and Kalu (2015), Orji, Waurika, and Umofia (2017), and Okumoko, Omeje, and Udoh (2018) across the sub-Saharan region have led the authors to enquire the pertinent roles indicators of infrastructure on the industrial growth process, particularly in the case of SSA.

2.4.2 The Endogenous Growth Theory Linking To the Study

This literature widely attests to the effects of human capital skill development on economic output growth. Becker (1962) posits that human capital enhances output growth via skill acquisition. Becker's theory explained the broader influence of human capital skills. The theory emphasised that the roles of human capital skills were beyond the direct influence on output growth; instead, they spread the skills across other factors of production, such as indicators of infrastructure, to achieve industrial output growth.

In support of Becker (1962) and as the pioneer and advocate of endogenous growth theory, Romer (1983) came up with internal perspectives for achieving output growth. Romer used his 1983 and 1986 works to emphasize ideas and knowledge as the essential tools of output growth. Similarly, Lucas (1988) stated that an individual stock of knowledge raises productivity growth by acquiring more productive skills with a suitable investment in human capital. Lucas argued that decentralized models must be utilised more because the accumulated individual skills cannot be transferred to the larger economy. Therefore, there is a need to strike a balance regarding investment subsidy on this stock of knowledge to curb possible externalities to produce socially optimal units of human capital skill. In the 1990s, other followers came up with different views; Barro and Lee (1993) aligned with the views of the endogenous growth model as postulated in Romer (1990), specifically on the need to improve human capital investment toward achieving economic growth. Rebelo (1991) opined that continuous growth is accomplished through different combinations of endogenous inputs, which can be stocked without diminishing returns. "To effectively inject human capital skill and physical capital K as inputs factor of output growth, Mankiw, Romer, and Weil (1992) and Lucas (1988) came up augmented endogenous model" as opposed to the neoclassical model formerly built by Solow and Swan (1956) - $Y=AK^{\beta} L^{\alpha}$ ……… (4), which failed to explicitly and endogenously integrate human capital skills and physical capital as endogenous factor inputs for output growth.

By challenging the neoclassical model, the Lucas-Romer growth theory emerged to draw more perspectives to the vital roles of human capital skill advancement. Lucas-Romer stresses the role of endogenous factors, which focus on the skills aspect of human capital along with other inputs to expedite output growth. Notably, the augmented endogenous model paved the way for the skill-focused human capital model as a determinant of output growth. This model disclosed the roles of human skills as significant actors of knowledge diffusion and the cause of innovative technology in catching up with the latest up-to-date job tasks (Romer, 1990; 1986; Lucas, 1988; Rebelo, 1991; OECD, 2018). Consequently, the endogenous theory underpins this study because it gives an adequate account of knowledge as a factor input alongside infrastructure technology that informs K as a determinant of output growth.

2.5 EMPIRICAL LITERATURE

Previous researchers have attempted to examine the link between economic growth and human capital or industrial drive and infrastructure. Whether previous researchers could link human capital, infrastructural development and industrial sector growth in the broader context remains unresolved. Notwithstanding, few of these previous studies related to this research's objectives, though with different focus and scope, shall be given priority.

2.5.1 Studies Related To How Factors of Human Capital Skill Development Determined Output Growth

There were earliest studies that tried to link human capital and output growth but without focusing on the skills aspect of human capital and how it determines industrial output growth across sub-regional economic blocs in SSA; for example, Mankiw (1995), Ndiaya and Lv (2018), Liu (2020), Keji (2021) and Huang et al. (2022) among others, made some frantic efforts but less focus on how the human capital skills determinants predict industrial output growth. Also, previous works could not account for the sub-regional determining factors of human capital skill development and their impact on sub-regional output growth across ECA ECCAS ECOWAS AND SADC in SSA. This study contributes to the literature by supporting sub-regional economies policy addressing perpetual limitations to industrial output growth at individual economic blocs in SSA. At this point, sub-regional specifics productive problems concerning output growth can be addressed with specific policy support across the various sub-economic blocs in SSA.

2.5.1.1 Related Studies outside African Economies

Mendes et al. (2011) investigated the influence of human capital on general output growth and firms' performances by disaggregating the output growth effects of human capital from that industrial productivity effect through a bi-disciplinary study in Portugal. These effects were measured using the within and the between different sets of surveys drawn. The empirical methods were divided into two sides' survey. The within approach measured how the human capital literature relates to output growth, while the within approach captured other literature that relates human resources within firms and firms' performance. Hence, it was revealed that human capital has dual effects regarding macro and micro-productivity growth. Mendes et al. emphasised that present human capital studies influence firms' productive strength due to systematic human capital advancement contributing to organisational success.

Chani et al. (2021) adopted Fully Modified Ordinary Least Square (FMOLS) to investigate the effect of human capital investment on output growth in Muslim and Non-Muslim Asian regions. The results show that human capital indicators have positive effects on output growth. For example, human capital indicators such as education expenditure, labour force and health expenditure significantly impacted output growth. Bhatti and Abdul Ghafoor Awan (2019) looked inwardly to consider the socioeconomic determinants of human capital through school enrollment in Pakistan. The study revealed through Ordinary Least Square (OLS) that low school enrollment significantly impacts the Pakistani economy, attributed to poor socioeconomic productivity, set-up, and dilapidated learning facilities. Therefore, the authors posited that government infrastructure should be set up across public schools to improve future productivity in Pakistan. Perepelkina, Perepelkinaa and Morozovaa (2016) examined the evolution of the concept of human capital in an economy. The writers showed the extent to which the human capital structurally and intellectually changes over time and affects economic science. It was hypothesized and formulated that human capital is the propeller of economic advancement. Moreover, it was later discovered that human capital evolved through a cause-effect nexus, necessitating productivity growth. Meanwhile, Shah, Hussain, and Hussain (2017) examined the Skill Gap Analysis in Pakistan's Ship Breaking Industry. The study adopted a schematics approach to examine different perspectives of safety measures skills applicable by graduates across education, health, and demands of TEVT graduates to reveal that improved skilled graduates significantly influence the product performance of the breaking industry in Pakistan. The implication is that knowledge plays a vital role in productive activities, as Ghahroudi et al. (2019) echoed by disaggregating knowledgeable skills into three scopes: acquired knowledge, shared knowledge, and accountable knowledge, which are pertinent to profitability and productivity.

Also, Kutu and Ngalawa (2016) examine short- and long-run factors affecting production and industrial production in Brazil, Russia, India, China and South Africa (BRICS) through the panel Autoregressive Distributed Lags (P-ARDL). The study showed evidence of long-run and short-run nexus between industrial production and factors affecting production across the BRICS. Keng, Lin, and Orazem (2017) examined the effects of access to college on graduate quality in Taiwan through a weighted least square approach. The scholars revealed that college graduates' share of the labour force rose significantly, which influenced technology growth in Taiwan. The study submitted that work experience was essential in securing the needed jobs.

Meanwhile, Liu (2020) investigated the promotion of industrial structures along “Belt and Road” countries between 1995 and 2018. The study adopted panel data to establish that human capital influences industrial structure via quality and quantity labour forces. The study submitted that labour efforts are significant to industrial sector growth. Thuong (2020) investigated the expansion of the industrial linking cluster in Vietnam to resolve the fact that industrial cluster linkages have developed without significant control because the linking cluster is loose and inconsistently operating.

2.5.1.2 Studies within African Economies

Mohamed, Abd El-Aziz, and Ramadan (2021) investigated the effect of human capital on output growth in Egypt between 1995 and 2018. The outcome revealed that human capital indicators have an insignificant effect on output growth in Egypt through Autoregressive Distributed Lag analysis (ARDL). The study disclosed that education has a positive link with an insignificant effect on Egyptian output growth, while other indicators like health have been proven to harm Egyptian output growth. The scholars attributed the result to poor infrastructural network, weak institutional structure and inability to transform knowledge into productivity in Egypt. Meanwhile, in a related study, Anyanwu (2017) investigated the effects of manufacturing value (MVA) added on the North African economic development between 1990 and 2014, using pooled panel Ordinary Least Square (POLS) and inverse two most miniature Square (IV-2LS) techniques to reveal that MVA has significant effect on the north African economic development. Aerts and Haezendonck (2017) developed the inter-organisational knowledge transfers (IOKT) model to study the effectiveness of knowledge transfer across different organisational settings through public-private partnerships (PPP). The study revealed that seeking and distributing knowledge via PPP-related knowledge points in public organisations enhances general decision-making towards output growth. The findings uncovered the effectiveness and efficiency of inter-organisational knowledge transfer for proficient productivity.

2.5.1.3 Studies within the Sub-Saharan African Economies

Bokana and Akinola (2017) and Mbonigaba and Akinola (2019) used higher education outcomes and school enrollment at a higher level to capture human capital skills on productivity effects in Sub-Sahara Africa between 1981 and 2014. Least Square Dummy Variable and System Generalised Moment Methods were used to reveal the significant and direct impact on productivity across the twenty-one selected countries. Okumoko, Omeje, and Udoh (2017) posited that human capital indicators negatively impact industrial sector growth, according to the study of human capital dynamics and industrial development in Nigeria. The authors explored Johansen's cointegration method to estimate secondary data drawn between 1976 and 2016. Meanwhile, a related study by Raheem and Adedeji (2008) assessed the human capital development, resource rent and inclusive growth in sub-Sahara Africa. Working on the data set obtained from 18 SSA countries, it was discovered that human capital indicators such as education and health were significant in output growth. The study further carried out a simulation exercise, which indicated that increasing government spending would increase GDP per capita growth by thirteen per cent. Msweli (2015) argued what South Africans can learn from Botswana regarding Human capital development. Msweli adopted comparative analysis across the four central pillars of a human capital index such as education, health and wellness, working population, and conducive environment, to unravel that though both countries had negative human capital scores, Botswana had more HCI scores than South Africa, which was an implication for future policy formulation and implemented in South Africa.

Meanwhile, Keji (2021) studied the link between human capital and output growth in Nigeria and discovered that human capital significantly affects output growth through ARDL and ECM techniques. Okon (2022) studied savings as the function of human capital development among resource-rich countries across SSA through the Autoregressive Moving Average (ARMA) technique. The study unravels that gross savings across resource-rich countries are negative and significantly influence human capital development.

2.5.2 Studies Related To How Factors of Infrastructure Development Determined Output Growth

Here, having considered the human capital side of the factors, it is pertinent to review the factors of industrial output growth from the infrastructural side. That is, using infrastructural development as one of the key factors determining industrial growth across different regions to disclose the gaps concerning the study's first objective.

2.5.2.1 Related Studies outside African Economies

Chowdhury (2012) posited that maintenance of critical infrastructure should be placed on performance-based maintenance contracting. This strategic approach can address most infrastructural maintenance challenges in developing countries. Wei and Wu (2021) investigated the effect of government-focused industrial clusters on efficient resource allocation with evidence across 30 provinces in China from 2000 to 2017. Hsieh and Klenow's resource mismatch theory was adopted. The study revealed a trend of "free-ride" instigated by government interference, which led to the U-shaped variation trend of industrial clusters on resource distribution effectiveness. This paper showed possible options towards improving efficient resource allocation through synergy between market mechanisms and minimum government involvement. Edziah et al. (2021) examined the impact of human capital on energy proficiency through panel data that cut across developing economies spanning from 1990 through 2017. The study adopted the stochastic frontier method and disclosed that human capital development promotes energy development through cleaner future energy management.

Sylvaire et al. (2020) investigated infrastructure development through Chinese investors' project investment in the Central African Republic. The study adopted trend analysis to establish China's investment's vivacious and significant impact on the Central African Republic's human capital skills and infrastructure development. Meanwhile, Muwanguzi et al. (2020) examined the modelling of the output growth trajectory of the Iron and Steel Industry in Uganda. The study adopted Dynamic Stochastic General Equilibrium Models (DSGE) to disclose a significant increase in Steel and Iron production in the current year and the next five years due to massive infrastructural investment in Uganda's economy.

2.5.2.2 Related Studies within African Economies

Amoah and Jehu-Appiah (2022) investigated determinants of industrialisation in Africa through Two-Stage Least Square (2SLS) technique. The study revealed the insignificant effect of human capital on industrialisation in Africa—Ludé et al. (2020) Governance, infrastructure and regional integration across the CEMAC region. The authors adopted the Pseudo Maximum Likelihood method of the Fish Law (PPML) through data from 2006 to 2016 to reveal that governance significantly affects trade integration among CEMAC regions. Hence, the roles of governance in public expenditure on infrastructure cannot be over-emphasised, which is an implication of this study.

2.5.2.3 Studies within the Sub-Saharan African Economies

Emily and Muyengwa (2021) examined the effect of maintenance on infrastructural facilities around municipalities in Limpopo Province, South Africa. The authors adopted qualitative and quantitative analysis through structural interviews to disclose that poor maintenance culture influences the performance of the infarct structure in Limpopo. Conversely, using panel data analysis, Sultana, Rahman, Aderogba, and Adegboye (2019) investigated the link between road infrastructure and household well-being in Nigeria. The findings revealed that easy access to road networks significantly influences house living conditions. Fedderke and Luiz (2005) analyzed economic infrastructure investment in South Africa through F-tests adopted to ascertain directions of nexus in line with Pesaran, Shin and Smith, 1996, 2001. The study revealed a bi-directional nexus between infrastructure and economic advancement in South Africa.

Consequently, the findings suggested that the inability to prioritize vital infrastructure over time is responsible for the inadequate infrastructure for overall economic progress. At the same time, Orji, Worika and Umofia (2017) estimated the impact of infrastructural progress on Nigeria's industrial sector through Ordinary Least Squares (OLS). The results showed that infrastructural improvement has insignificant effects on the Nigerian industrial sector. This is an implication for this study, as Nigeria has one of the largest economies in SSA with poor infrastructural spread. Hence, there is a disconnection between infrastructural development and industrial sector growth in Nigeria.

2.6 SUMMARY AND GAPS FROM THE RELATED STUDIES FOR OBJECTIVE ONE

The literature related to objective one has been adequately explored in chapter two across the globe, including Africa and sub-Saharan Africa. At this point, it is pertinent to summarise the gaps discovered.

Perepelkina, Perepelkinaa, and Morozovaa (2016) studied the evolution of the human capital concept in economics. The writers showed the dynamic nature of human capital regarding structure and intellect over time and its broad effect on economic science. The study hypothesized that human capital propelled economic advancement. Moreover, they later discovered that human capital evolution worked through the cause-effect relationship that expedited productivity growth.

Meanwhile, Shah, Hussain, and Hussain (2017) investigated the skill gap in Pakistanis in the shipbreaking industry through sample survey analysis to conclude that the higher skilled are less exposed to hazardous work tasks. The writers argued that a conducive work environment contributes to high productivity. Keng, Lin, and Orazem (2017) examined the effects of access to college on graduate quality in Taiwan through a weighted least square approach. The scholars revealed that college graduates' share of the labour force rose significantly, influencing technology growth in Taiwan. The study submitted that work experience was necessary for securing needed jobs.

Similarly, Ghahroudi, Hoshino, and Ahmadpoury (2019) studied the effect of Knowledge Management Orientation on New Product Commercialization via the interceding function of market coordination in 700 Iranian firms. Findings from the study reveal significant effects of knowledge management and market orientation on productivity performance, improving new product commercialization. Liu (2020) investigated Promoting industrial structure along "Belt and Road" countries between 1995 and 2018. The study adopted panel data to establish that human capital influences industrial structure via quality and quantity labour forces. Bhattacharya and Bhattacharya (2018) studied the new Institutional Design for Infrastructure sustainability through feasible financial stability in the Pan-Asian region. The study suggested multicurrency Bonds for sustainable infrastructural investment in Asia. In a related study, Emily and Muyengwa (2021) examined the effect of maintenance on infrastructural facilities around municipalities in Limpopo Province, South Africa. The authors adopted qualitative and quantitative analysis through structural interviews to disclose that poor maintenance culture influences the performance of the infarct structure in Limpopo.

Shahrivar et al. (2022) examined the prioritization of infrastructural maintenance through a comparative analysis of the Fuzzy theory in multi-decision making (MCDM). The study adopted MCDM methods to empirically compare maintenance strength in a fuzzy environment, which revealed diverse maintenance levels. Similarly, Tortorelli et al. (2022) studied the optimal configuration of critical infrastructures through decision backing. The authors adopted a decision support system to recommend possible configurations and protection for critical infrastructure.

Stoichev (2014) adopted the L-strategy to protect critical infrastructures and individuals against terrorist attacks in a society. The study established several strategic methods for securing the EU's individuals and infrastructure.

Du et al. (2022) assessed how investment in different infrastructures affects China's economic output worth. The researchers resolved that investment in infrastructure supports the quality of economic output in China. Meanwhile, Ajayi (2007) concluded that industrial spatial patterns are subject to the applicability of industrial linkages in product authorization, which was a major driving seat for industrial growth. The findings examined recent trends and spatial patterns of productive industry in Nigeria. Productivity flows were examined via artisans' set-up, and upward growth grew to large-scale production. Hence, the study suggested that productivity growth can be sustained in Nigeria through proactive industrial privatization. Edun et al. (2013) examined the effects of infrastructural development on the Nigerian economy. The authors employed simple foreign investment of diversified equilibrium to conclude that infrastructural effects on economic output in Nigeria were at the lower state.

In contrast, Bennett et al. (2015) posited that industrial advancement has an insignificant impact on Nigerian economic output growth. Ordinary Least Square (OLS) was adopted to investigate the influence of industrial development on economic growth between 197 3 and 2013. Hence, the authors suggest that the government should put fair and plain level playing measures in place for rapid industrialisation in Nigeria. In another related study, Abdulqadir and Asongu (2021) examined the lopsided effect of infrastructural technology (i.e., access to the Internet) on economic growth across forty-two sub-Saharan countries between 2008 and 2018. The researchers adopted dynamic panel data analysis to conclude that access to internet access as a form of technology influenced economic growth across the 42 SSA countries.

Branson and Leibbrandt (2013) measured the impact of educational attainment on labour market outcomes from 1994 to 2010 with evidence from South Africa. The findings showed that the national household index of higher education is strongly associated with the labour market and the chances of securing white-collar employment. Meanwhile, Okumoko, Omeje, and Udoh (2018) posited that human capital indicators negatively influence industrial sector growth by studying human capital dynamics and industrial development in Nigeria. The authors adopted Johansen's cointegration method to estimate secondary data drawn between 1976 and 2016. Okon (2022) studied savings as the function of human capital development among resource-rich countries across SSA through the Autoregressive Moving Average (ARMA) technique. The study unravels that gross savings across resource-rich countries are negative and significantly influence human capital development. According to Okon (2022), the outcomes of this nature could be traced to the bad savings culture of the past governments in SSA countries.

Consequently, diverse views on the studies linking factors determining industrial output growth from the literature have a different focus from this study. Also, the literature reviewed showed limited studies investigating the determinants of industrial output growth via human capital skills development and infrastructure in SSA. This study intends to contribute to the body of knowledge in multiple-folds. Firstly, this study accounts for skills as an endogenous source of human capital and its determinants on output growth in SSA. Secondly, the study tried to classify productive infrastructure from non-productive infrastructure by narrowing down specific economic returns to scale infrastructure that can expedite industrial sector growth in sub-Saharan Africa. Thirdly, this study tries to empirically contribute to the literature by adopting a system-generalised method of moment conditions to ascertain which specific infrastructures have a higher return to scale on industrial output through the past and the present periods. The dynamic nature of the system GMM is the best option to address possible endogeneity, simultaneity and time path effects of factors on industrial output. Also, household consumption is a precondition for conducive working conditions to maximize industrial output growth. Fourthly, the study disaggregated system GMM into short-run system GMM and long-run system GMM. This is to account for the short-run and long-run impact of factors determining industrial output growth. This makes the study unique and cannot be found in most early works, as few related works mostly stopped at the short-run system GMM analysis. Lastly, this study designed school enrolments across all levels in the model building as a collective source of knowledge to provide key policy support for output growth across individual economic blocs in SSA, where assimilation h, denoted in the model, was meant to capture sources of knowledge. Meanwhile, k in the model caters to the possible progression of infrastructural technology. The combined effects of knowledge and tech in the model building paved the way for knowledge diffusions for higher industrial output growth, all equal things.

2.6.1 Contributions to the Literature through Objective One

Generally, it appears that the mechanisms of factors determining output growth used by early writers such as Huang et al. (2022), Okon (2022), Keji (2021), Akinola and Mbonigaba (2019), Bokana and Akinola (2017) seem lopsided because they failed to account for crucial patterns of factors determining industrial output from endogenous point of view, despite diverse results from previous works, which are implications for the first objective. Also, the complementarity effects of the critical indicators of human capital skills and infrastructure seem scanty among extant empirical literature.

Consequently, this study systematically contributes to the literature by identifying the needed determinants of industrial output growth in SSA. In achieving the first objective, the opportunity cost of knowledge acquisition and household consumption as the basis for conducive working conditions were endogenously incorporated to derive a knowledge-based model for industrial sector growth through short-rung and long-run system GMM across SSA countries. Using opportunity cost and household consumption indicators as preconditions for improved industrial output growth was unique. Also, the study contributes to the body of knowledge. Firstly, by focusing on skills as endogenous sources of human capital and Physical capital and how they determined output growth in SSA. Secondly, pre-estimation techniques such as summary statistics and correlation matrix accounted for robust determinants of industrial output growth to curb possible collinear problems in the study. Thirdly, the study disaggregated system GMM into short-run system GMM and long-run system GMM to ascertain factors determining industrial output growth. This makes the study unique and cannot be found in most early works, as few related works mostly stopped at the short-run system GMM analysis.

2.7 RELATED STUDIES ON HOW COMPARATIVE EFFECTS OF HUMAN CAPITAL SKILL DEVELOPMENT AND INFRASTRUCTURAL DEVELOPMENT AFFECT INDUSTRIAL SECTOR GROWTH ACROSS THE SUB-REGIONAL ECONOMIC BLOCS IN SSA.

Here, it is pertinent to review the studies that link human capital and infrastructural development to industrial growth across different regions to reveal the gaps concerning the second objective in the study**.**

There were past studies that tried to establish the link between human capital, infrastructure and output growth; for example, Mankiw (1995), Fedderke and Bogetić (2006), Abdulazeez and Naim (2018), Lin (2019) and Du Zhang, and Han (2022) among others, made some frantic efforts but with less focus on the aspect of the effects from human capital skill and infrastructure on industrial output growth across EAC ECCAS ECOWAS and SADC. The common resolves among the past studies cut across a country case study with less attention on comparative analysis across sub-regional economic blocs within SSA. Also, previous studies could not compare the comparative effects of human capital skills and infrastructure on sub-regional industrial sector growth through trend estimation, robust sub-sample analysis and Fixed Least Square Dummy Variable (FE-LSDV) across EAC ECCAS ECOWAS and SADC which are the focus of this study.

2.7.1 Related Studies outside African Economies

Jiang (2022) examined industrial linkages among industries in the province Y region across China through an internal and direct industrial correlation approach. The study attributed poor industrial linkages in Chinese Y province to low human capital skills and an unorganized industrial structure. Hoja and Mohamed (2022) examined Industrial Clusters and their Role in Enhancing the Competitiveness of Small and Medium Enterprises-Leather and Footwear Sector in Palestine through the Partial Least Squares Structural Equation technique. The study revealed that Perceived Location Doubt and national philosophy significantly affect industrial clustering.

Thamma-Apiroam (2015) adopted a theoretical approach to assess the concept of human capital and its measurement along the strata of cost, income and output in the Thailand economy. Literature synthesis and causality test via quantitative data analysis from 1980 to 2010. According to Thamma-Apiroam, Thailand's output growth and human capital indicators had a bi-directional relationship. Hence, the study further suggested that quality education and increasing education opportunities are necessary for Thailand's output growth. Du et al. (2022) examined investment in infrastructure to predict the level of output growth in China. The researchers revealed that investment in infrastructure promotes the quality of economic output through the two-stage least squares (2SLS) technique. Huang, Zeng, Wang, and Zhang (2022) used knowledge spillover and high-tech industry models Moran index econometric analysis to examine the relationship between scientific, high-tech innovations and economic growth. The study revealed that the knowledge spillover effect is weak against high-tech effects on industrial agglomeration. Meanwhile, Ngai and Samaniego (2009) studied research and productivity growth across different industries in the United States of America through multi-sector knowledge production modelling. It was discovered that long-run differences subsisted in research and development intensity and productivity growth across the selected industries based on their consumers' choices, primarily preceded by changing technological opportunities. Jones (2019) assessed the strength and non-rivalry of the Romer model, which incorporated innovative and infrastructural technology into macroeconomic modelling. The study showed how endogenously, productivity improved via incorporating technological innovation, giving rise to general industrial output growth for profit-maximizing firms.

2.7.1.1 Related Studies within African Economies

Edziah, Sun, Anyigbah, and Li (2021) investigated the impact of human capital on energy efficiency across developing countries between 1990 and 2017 through the energy demand and stochastic frontier models. The authors disclosed that human capital significantly affects energy indicators across the selected countries. Anyanwu (2017) investigated the effects of manufacturing value (MVA) added on the North African economic development between 1990 and 2014, using pooled panel Ordinary Least Square (POLS) and inverse two least Square (IV-2LS) techniques to reveal that MVA has a significant effect on the north African economic development.

Consequently, the notable gap in the sub-section disclosed that most of the related studies from outside SSA have not been able to address the comparative effects of human capital skills and infrastructure on industrial output growth, which is one of the focuses of this study.

2.7.1.2 RELATED STUDIES WITHIN THE SUB-SAHARAN AFRICAN ECONOMIES

Fedderke and Luiz (2005) posited that infrastructure has mixed effects on South African economic growth. In another related study, Alani (2018) examined the advancement of output growth and development via human capital and technology development in Kenya. The study employed a Generalised Least Square (GLS) approach to submit that human capital and technological progress significantly impacted Kenyan productivity advancement.

Bogetić and Fedderke (2006) studied South Africa's infrastructure performance across four major areas-electricity, water sanitation, transportation and information technology against 207 countries to reveal that South Africa performs better regarding expected quality but poor in terms of access to these infrastructures, especially in the rural areas. The study benchmarked the quality of infrastructure in South Africa through comparative analysis alongside other higher-income countries, suggesting that South Africa needs to invest in scaling up its infrastructure to catch up with advanced countries.

Wonyra (2019) adopted fixed and random effects analysis via Hausman and Taylor criteria to examine the roles of human capital through structural change for industrialisation in sub-Sahara Africa. The study showed that human capital strength propelled manufacturing sector growth, accelerating industrial sector growth. Fawehinmi, Omolade, and Keji (2019) examined the impact of human capital and capital goods import on output growth in sub-Sahara Africa through a panel-ARDL analysis of 30 countries. The empirical findings showed that capital goods import positively influences output growth, while human capital has an insignificant but positive effect on productivity growth in SSA. Also, trend analysis and correlation outcomes disclosed a weak link between human capital and capital goods for output growth. Hence, the authors suggest that the effective spread of knowledge catalysts quality capital goods for output growth to be achieved, especially in a sub-region that is characterized by primary sectors.

Ludé and Thérèse (2020) examined the impact of governance on physical infrastructure across the CEMAC region through the Pseudo Maximum Likelihood approach. The study concludes that governance significantly affects inter-regional infrastructure development across the CEMAC despite being a barrier to regional integration. Meanwhile, in another related study, Abdulqadir and Asongu (2021) examined the lop-sided effect of access to the Internet on economic growth across forty-two sub-Saharan countries between 2008 and 2018. The researchers adopted a two-step difference General Method of Moment dynamic panel data analysis to conclude that access to internet access as a form of infrastructural technology influenced economic growth across the 42 SSA countries. Meanwhile, Akinlo (2020) studied sub-Saharan Africa's fourth industrial revolution and economic output growth. The Pooled OLS, Fixed Effect, Random Effect, and GMM techniques show that technological progress does not significantly impact growth in sub-Saharan Africa. Hence, the disconnection between factor productivity and economic output progress requires higher education for vital skills in SSA.

In another related study, Abdulqadir and Asongu (2021) examined the lop-sided effect of infrastructural technology (i.e. access to the Internet) on output growth across forty-two sub-Saharan countries between 2008 and 2018. The researchers adopted dynamic panel data analysis to conclude that access to the internet access as a form of technology influenced economic growth across the 42 SSA countries. Meanwhile, Ajayi (2007) concluded that industrial spatial patterns are subject to the applicability of industrial linkages regarding product authorization, which was a primary driving seat for industrial growth. In the findings, recent trends and spatial patterns of productive industry in Nigeria were examined, where productivity flows were examined via artisans' set-up and upwardly grew to large-scale productivity. Hence, the study suggested that productivity growth can be sustained in Nigeria through proactive industrial privatisation. Fedderke and Bogetić (2006) used the Pooled Mean Group (PMG) test of Pesaran, Shin and Smith (PSS) 1999 to explore both the direct and inverse effects of public infrastructure on economic output in South Africa. The explored contradiction analysis to disclose how public infrastructure crowds out private infrastructure in South Africa. Abdurraheem and Naim (2018) studied Gaps in types of infrastructural spending in Sub-Sahara Africa. The authors posited that the impact of Sukuk instruments for infrastructural funding is minimal. Hence, there are wider gaps in the types of infrastructural funding in SSA.

2.7.2 Summary and Gaps from the Related Studies for Objective Two

In the meantime, Zhang (2018) accounted for the link between the synergic and Regional Science-Tech Innovation (STI) in advancing strategic means of emerging Industries in Guangdong Province. It was established that synergic platform-driven science technology innovation intensity via coupling among the emerging firms is low, which reduces industrial spillover. Therefore, the study suggests a scientific basis for actualizing synergistic coupling to boost optimized STI in construction industries across Guangdong Province. In comparison, Wei (2017) studied the importance of building investment in infrastructure across the Asian Bank industry through trend analysis. The author concludes that investment in infrastructure within the Asian bank industry significantly stimulates living conditions via financial stability and accelerates economic growth in the Asian region.

Lin (2019) emphasised the need to transform acquired human capital skills into practice for industrial output growth through Knowledge review and research in Knowledge Management. The study concluded that Knowledge is crystalized into management, creation, storage, transfer, and application toward industrial output growth. Meanwhile, Johnson Ong (2004) posited that knowledge influences productivity growth, particularly in the pre-production stage, during-production stage and post-production processes in a knowledge-based economy (KBE) through the Needs Analysis technique to discover knowledge as the source of innovation in Singapore. Meanwhile, Shah, Hussain, and Hussain (2017) investigated the skill gap in Pakistanis in the shipbreaking industry through sample survey analysis to conclude that higher-skilled people are less likely to do hazardous work tasks. The writers argued that a conducive work environment contributes to high productivity. Liu (2020) investigated Promoting industrial structure along "Belt and Road" countries between 1995 and 2018. The study adopted panel data to establish that human capital influences industrial structure via quality and quantity labour forces. Therefore, the study emphasised the need to optimize age structure to promote education for sustainable industrial structure.

Meanwhile, Ajayi (2007) concluded that industrial spatial patterns are subject to the applicability of industrial linkages in product authorization, which was a primary driving seat for industrial growth. The findings examined recent trends and spatial patterns of productive industry in Nigeria. Productivity flows were examined via artisans' set-up, and upward growth grew to large-scale production. Hence, the study suggested that productivity growth can be sustained in Nigeria through proactive industrial privatization. Edun, Akinde, Jolaleye, and Idowu (2013) examined the effects of infrastructural development on the Nigerian economy. The authors employed simple foreign investment of diversified equilibrium to conclude that infrastructural effects on economic output in Nigeria were at the lower state. In another related study, Abdulqadir and Asongu (2021) examined the lop-sided effect of infrastructural technology (i.e., access to the internet) on economic growth across forty-two sub-Saharan countries between 2008 and 2018. The researchers adopted dynamic panel data analysis to conclude that access to internet access as a form of technology influenced economic growth across the 42 SSA countries. Muvawala (2018) worked on industrialisation as a vehicle for Vision 2040 in Uganda via infrastructural spread within the sub-sector of productive firms using the trend analysis. The study posited that infrastructural spread within the sub-sector of productive firms affects industrial sector growth in Uganda.

Meanwhile, Eigbiremolen and Anaduaka (2014) studied human capital through government spending on education to conclude a positive relationship between economic growth and human capital. Bojana and Akinola (2017) and Akinola and Mbonigaba (2019) used higher education upshots and school enrollment rates at a higher level to proxy human capital skills on productivity effects in Sub-Sahara Africa between 1981 and 2014. Least Square Dummy Variable and System Generalised Moment Methods revealed the significant and direct impact on productivity across the twenty-one selected countries. Okumoko, Omeje, and Udoh (2018) posited that human capital indicators negatively influence industrial sector growth by studying Nigeria's human capital dynamics and industrial development. The authors adopted Johansen's cointegration method to estimate secondary data drawn between 1976 and 2016.

Meanwhile, Otalu and Keji (2015) examined Nigeria's determinants of industrial sector growth through the Cointegration and error correction model approach. The study identified gross capital formation, labour force, school enrollment, and access to electricity generation as key determinants of industrial growth in Nigeria. The outcomes revealed that all the determinants have more of a permanent effect on industrial output growth than a transitory effect.

Consequently, diverse views on the studies linking human capital and infrastructure with industrial output growth from the literature have a different focus from this study. Also, the literature reviewed shows limited studies investigating the spillover effect of human capital skills and infrastructure development on industrial sector growth across EAC, ECCAS, ECOWAS and

SADC in SSA. Notably, this study intends to contribute threefold to the body of knowledge. Firstly, none of the reviewed works studied comparative factor inputs as a source of human capital skill and infrastructural-tech and their effects on industrial output growth across sub-regional economic blocks in SSA. Notably, some studies like Fedderke and Luiz (2005), Mbonigaba and Akinola (2019), Rangongo and Ngwakwe (2019), and Akinola and Mbonigaba (2020), Friedrichs, Keeton and Rogan (2021) emphasised more on the lopsided roles of human capital and infrastructure on output growth, not specifically focusing on human capital skill and infra-tech spillover effects on industrial output growth, while some of the other related studies were conducted in some distance years back, which might not address the current problems confronting SSA's industrial sector growth. Secondly, the studies try to re-modify the augmented endogenous model to account for robust spillover of knowledge-deepening by incorporating household consumption and opportunity cost in the model building to account for control factors via skill-creation, time-path skill and skill spread, respectively. This is because skill spillover takes time to manifest in human capital, and the motivation around this skill is pertinent for industrial output growth. Thirdly, the study adopted trend analysis, sub-sample, and least square dummy variable techniques to compare spillover effects across sub-regions. The study empirically accounts for spillover from human capital skill and infrastructure development and their effects on industrial sector growth.

In summary, findings from this study contribute to the literature by examining the comparative effect of human capital skills and infrastructure development on industrial sector growth across EAC, ECCAS, ECOWAS and SADC in SSA via the trend analysis, FE-LSDV techniques and disaggregated system GMM. Also, among other relevant indicators, the study measured human capital skills development through the time-factor indicator like opportunity cost as an internal instrument (i.e., alternate forgone for a time loss while seeking knowledge) and household consumption, i.e. conducive working conditions as a pre-condition for improved skill acquisitions to work-through knowledge-based model as an internal instrument for output growth across sub-regional blocs in SSA. Pertinent infrastructural indicators were well estimated. Finally, the study adopted trend analysis, sub-sample and Least Square Dummy Variable techniques to establish the comparative impact of the individual sub-regional human capital skill and infrastructural techs across SSA. This analysis is unique among the mainstream studies, which makes this study unique.

The study adopted the system GMM as a confirmatory technique to ascertain the dynamic effects of human capital skill and infrastructure on industrial output growth. The following section introduces the suitable methodology adopted in the study to achieve our objective via data obtained from the selected countries.

2.7.2.1 Contributions to the Literature via Objective Two

Consequently, based on the scarce study that links human capital skills, infrastructural development and industrial output growth. This study contributes to the literature by analyzing the comparative effects of human capital skill and infrastructure development on industrial output growth across sub-regional economies in SSA, using the robust sub-sample analysis and FE-LSDV. Moreover, the study systematically measured the comparative effects of human capital skills and infrastructure techs on industrial output growth using a two-step system GMM as a confirmatory technique. Also, the study adopted trend analysis, robust sub-sample, and least square dummy variable (FE-LSDV) techniques to compare country-specific comparative effects across sub-regional blocs in SSA. Studying in this direction paved the way for individual sub-regional policy drafts towards industrial sector advancement, expanding the narrow range of industrial goods across SSA sub-regions. The study tried to re-modify the augmented endogenous model to account for robust comparative effects of knowledge-deepening by incorporating household consumption and opportunity cost in the model building to account for control factors via skill technology-creation, time-path skill and skill spread, respectively. This is based on the premise that acquired skill and skill-techs via comparative effects take time to manifest in human capital and infrastructure, and the motivation around this skill is pertinent for industrial output growth. The study empirically accounts for the comparative effects of human capital skill and infrastructure development and their effects on industrial sector growth in the short and long run.

2.8 RELATED LITERATURE ON THE ASYMMETRIC AND THRESHOLD EFFECTS OF KEY HUMAN CAPITAL SKILLS AND INFRASTRUCTURE INDICATORS

Different academic works on the related studies on asymmetric and threshold effects were reviewed in line with their regions within and outside the sub-Saharan Africa region. Hence, the leading ones among these empirical works are considered.

2.8.1 Related Studies outside African Economies

Du et al. (2023) worked with the industry life cycle theory to investigate the impact of subsidies in the renewable energy industry on industry development in China, using threshold regression models. The study established an inverted U-shaped nonlinear relationship between government subsidies and industrial output development in China.

Sama et al. (2023) examined the dynamics of human development and economic output growth on crude oil production levels via ARDL and NARDL models, with data from 1977 to 2019. The study established both linear and non-linear relationships among the series. The outcomes showed that CO2 emissions and output growth negatively affected crude oil production (COP) in the long run, while the human capital index and inflation positively affected crude oil production. Also, output growth and human capital disclosed a nonlinear effect on COP in the short run, while inflation and CO2 emissions exhibited a non-linear influence on COP in the long run. Mohamedameen et al. (2024) studied the threshold effects of inflation on the output growth in Iraq spanning from 2004 to 2022, using threshold regression analysis. The study revealed that inflation has a nonlinear impact on output growth in Iraq. The study resolved that the inflation threshold below 8% per cent proved positive and significant for output growth, while inflation above 8% hurts the output growth in Iraq.

Using the fixed effect technique, Ramadhaniyati et al. (2023) investigated the Threshold influence of Indonesian inflation on output growth spanning from 2014 to 2022. The study revealed that the non-linear inflation threshold has double effects on output growth below and above 2.11 per cent. The below threshold effect is reported to be positive and statistically influences output growth, while the threshold effect negatively and statistically affects output growth.

Harnani et al. (2022) studied the link between human capital in natural sustainability and output growth in Indonesia through a symmetric Autoregressive Distributed Lags technique. The study reported mixed symmetric effects of human capital and natural resources on short and long-run output growth. Qamruzzaman (2023) investigated the asymmetric link between education, clean energy, inward foreign direct investment (FDI) and good governance in China from 1997 to 2018 through Asymmetric ARDL and cointegration techniques. The study revealed the explanatory variables' positive and statistically significant non-linear impact on China's foreign direct investment (FDI) inflow. Tang and Kogid (2022) worked on asymmetric reactions from energy use in Malaysia via technology innovations, output growth and financial stability. The study adopted the non-linear ARDL technique to ascertain two regimes' effects of the explanatory variables on energy consumption in Malaysia. The short-run and long-run asymmetrical effects were established in the study.

Özaydin, Özgür and Dağdemir (2023) investigated the impact of capital formation on industrial production in India through Autoregressive Distributed Lag (ARDL). The study disclosed both short-run and long-run effects of capital formation on industrial output in India. Meanwhile, Alam (2023) worked on the impact of human capital on output growth in India, using the ARDL estimating technique from 1972 to 2019. The study concluded that human capital has a long-run significant effect on growth in India. Hongzhong et al. (2018) examined the effect of technological innovation and infrastructure on industrial growth in Bangladesh through ARDL and Granger Causality estimating techniques. The study disclosed the long-run impact of infrastructure and technological innovation on industrial growth from 1974 to 2016. Notably, infrastructure exhibited a positive and significant long-term impact on industrial growth in Bangladesh, while technological innovation disclosed a negative and significant long-term effect on industrial growth. Interestingly, the key variables exhibited positive and significant short-run effects on industrial growth in Bangladesh.

Hao (2023) examined the dynamic link between foreign direct investment, trade openness, capital formation and industrial output growth in China through the Autoregressive Distributed Lags Approach. The study established long-run relationships between indicators of foreign direct investment, trade openness, capital formation and industrial output growth in China. Meanwhile, Bouattour et al. (2024) investigated the threshold impact of technology import on industrial employment across advanced and less advanced countries through Panel Smooth Transition Regression. The study disclosed a positive threshold effect at above 13.667% in advanced countries, while adverse threshold effects were recorded at 3.44% in less developed countries.

2.8.1.1 Related Studies within African Economies

Ndoricimpa (2017) examined the threshold influence of inflation on output growth across Africa through the dynamic panel Threshold regression technique. The study disclosed the non-linear effect of inflation on output growth across the African region. Nkemgha et al. (2022) assessed the financial development and human capital thresholds on the infrastructure development-industrialization across 33 African countries between 2003 and 2019. The study disclosed direct and indirect threshold effects of infrastructure, financial development and human capital on African industrial sector growth through panel system GMM.

Dramani et al. (2023) examined how infrastructure uses through energy enhances human capital development in Africa, using the non-linear panel Autoregressive Distributed Lags Approach. The study revealed energy use's asymmetric long-run shock effect on African human capital. Meanwhile, Orji et al. (2020) analyzed the impact of human capital development on output growth in Africa's largest population country through the ARDL Approach. The study revealed the long-run impact of human capital on output growth. It was further disclosed that Boundary testing coefficients exhibited the presence of long-run links through higher F-statistics. Alshehry and Belloumi (2024) examined the symmetric and asymmetric effect of energy use and output growth on environmental development across Middle-East and North African countries through linear and nonlinear ARDL and Dumitrescu–Hurlin panel causality techniques. The study disclosed the long-run impact of output growth and energy consumption on environmental development and bidirectional causality between the indicators of energy use, output growth and environmental sustainability.

2.8.1.2 Related Studies within the Sub-Saharan African Economies

Sama et al. (2023) examined the dynamics of human development and economic output growth on crude oil production levels in Cameroon via ARDL and NARDL models, with data spanning from 1977 to 2019. The study established both linear and non-linear relationships among the series. The outcomes showed that CO_2 emissions and output growth negatively affected crude oil production (COP) in the long run, while the human capital index and inflation positively affected crude oil production. Also, output growth and human capital disclosed a non-linear effect on COP in the short run, while inflation and CO_2 emissions exhibited a non-linear influence on COP in the long run. Meanwhile, Woldu and Kanó (2023) studied whether there was a possible debt-threshold impact on per capita output growth in South Africa, using the threshold regression technique between 1960 and 2019. The study disclosed the non-linear effect of aggregate debt on output growth per capita in South Africa.

Odionye and Chukwu (2023) examined Asymmetric Reactions of Stock Prices and Industrial Output to Exchange Rate Shocks, using multiple threshold techniques from 1999 to 2021. The study disclosed that the asymmetric effects from the stock prices and industrial output caused depreciation in the exchange rate. Meanwhile, Ibrahim (2019) examines the effect of infrastructure on industrial output in Nigeria between 1981 and 2015 through dynamic ordinary least squares (DOLS) and Toda-Yamamoto modified Wald (MWALD)-based causality techniques. The study disclosed a positive and significant effect of infrastructure development on industrial output growth in Nigeria. Ogunjobi et al. (2021) assessed human capital and energy infrastructure on output growth in Nigeria, using data from 1981 to 2018. The study adopted ARDL and cointegration techniques to disclose that human capital and infrastructure significantly impact output growth in Nigeria.

Aisien and Ihensekhien (2020) examined the effect of capital goods import on manufacturing output in Nigeria using the Autoregressive Distributed Lags technique. The empirical outcomes revealed that capital goods import exhibited a long-run positive effect on manufacturing output in Nigeria. Meanwhile, Martha and Melikhaya (2022) investigated the link between human capital and output growth in Sub-Saharan Africa through the symmetric Autoregressive Distributed Lags and Error Correction Mechanism technique. The findings revealed a long-run relationship between human capital and output growth through school enrolment rate.

Wegari et al. (2023) examined the impact of human capital on Ethiopian output growth from 1980 to 2020 through Autoregressive Distributed Lags and Bound testing techniques. The findings revealed human capital's long-run statistically significant effect on Ethiopian output growth. Also, Njenga (2024) studied the consumption effect of infrastructure through electricity on output growth in Kenya. The study employed the symmetric Autoregressive Distributed Lags technique to conclude that electricity consumption positively affected output growth in Kenya. Meanwhile, using the qualitative literature review technique, Mpofu and Nemashakwe (2023) investigated the preparedness of the Zimbabwean Fourth Industrial Revolution. The study revealed low Human capital skills in the Zimbabwean mining industry, which was an implication for the fourth industrial era.

2.8.2 Summary and Gaps from the Related Studies for Objective Three

The empirical literature was well reviewed across studies from other regions of the world, within the African continent, and the sub-Saharan African region. This shows the precise stand of the previous findings in the cause of our empirical contributions to the extant literature.

Harnani et al. (2022) studied the link between human capital in natural sustainability and output growth in Indonesia through a symmetric Autoregressive Distributed Lags technique. The study reported mixed symmetric effects of human capital and natural resources on output growth both in the short and long run. Du et al. (2023) worked in line with the industry life cycle theory to investigate the impact of subsidies in the renewable energy industry on industry development in China, using threshold regression models. The study established an inverted U-shaped nonlinear relationship between government subsidies and industrial output development in China. Qamruzzaman (2023) investigated the asymmetric link between education, clean energy, inward foreign direct investment (FDI) and good governance in China from 1997 to 2018 through Asymmetric ARDL and cointegration techniques. The study revealed the explanatory variables' positive and statistically significant non-linear impact on China's foreign direct investment (FDI) inflow.

Özaydin, Özgür and Dağdemir (2023) investigated the impact of capital formation on industrial production in India through Autoregressive Distributed Lag (ARDL). The study disclosed both short-run and long-run effects of capital formation on industrial output in India. Meanwhile, Alam (2023) worked on the impact of human capital on output growth in India, using the ARDL estimating technique from 1972 to 2019. The study concluded that human capital has a long-run significant effect on growth in India. Hongzhong et al. (2018) examined the effect of technological innovation and infrastructure on industrial growth in Bangladesh through ARDL and Granger Causality estimating techniques. The study disclosed the long-run impact of infrastructure and technological innovation on industrial growth from 1974 to 2016. Notably, infrastructure exhibited a positive and significant long-term impact on industrial growth in Bangladesh, while technological innovation disclosed a negative and significant long-term effect on industrial growth. Interestingly, the key variables exhibited positive and significant short-run effects on industrial growth in Bangladesh.

Ogunjobi et al. (2021) assessed human capital and energy infrastructure on output growth in Nigeria, using data from 1981 to 2018. The study adopted ARDL and cointegration techniques to disclose that human capital and infrastructure significantly impact output growth in Nigeria. Aisien and Ihensekhien (2020) examined the effect of capital goods import on manufacturing output in Nigeria using the Autoregressive Distributed Lags technique. The empirical outcomes revealed that capital goods import exhibited a long-run positive effect on manufacturing output in Nigeria. Meanwhile, Martha and Melikhaya (2022) investigated the link between human capital and output growth in Sub-Saharan Africa through the symmetric Autoregressive Distributed Lags and Error Correction Mechanism technique. The findings revealed a long-run relationship between human capital and output growth through school enrolment rate.

Consequently, based on the scarce study linking human capital skills, infrastructural development and industrial output growth across economic blocs in SSA. Also, none of the early works duel much on the threshold and asymmetric effects of human capital skills and infrastructure on industrial output growth in SSA. The conceptual focus from the early studies was primarily different. For example, Hongzhong et al. (2018), Ogunjobi et al. (2021), Harnani et al. (2022), and Özaydin, Özgür and Dağdemir (2023) made frantic efforts to establish links between human capital, infrastructure and industrial development with less focus on skill-driven industrial output growth. Most of these studies came from other regions, while those around the SSA were based on single-country studies.

2.8.2.1 Contributions to the Literature via Objective Three

Based on the thorough study that links human capital skills, infrastructural development and industrial output growth across economic blocs in SSA. This study contributes to the literature by analyzing the threshold and asymmetric effects of human capital skill and infrastructure development on industrial output growth across sub-regional economies in SSA, using threshold regression and non-linear Autoregressive Distributed Lags (NARDL). Moreover, the study systematically measured the non-linear effects of human capital skills and infrastructure on industrial output growth in SSA. The study adopted Unit root via ADF and PP, CSD test, correlation matrix and Lag length criteria to fulfil all the necessary conditions before proceeding on non-linear techniques to ascertain the two regimes of human capital skills and infrastructure effects on industrial output growth across sub-regional blocs in SSA. Studying in this direction paved the way for individual sub-regional policy drafts towards industrial sector advancement, expanding the narrow range of industrial goods across SSA sub-regions, making this study unique.

2.9 SUMMARY OF GAPS FROM THE EMPIRICAL LITERATURE AND THE CORRECTIVE MEASURE TO FILL THE GAPS

To fill the notable vacuums from the empirical literature and to achieve all the set objectives in the study, this study fulfilled all the necessary conditions for panel data analysis through three major pre-estimation tests. The study carried out a preliminary investigation into the critical panel data sets to achieve unbiased estimates in our study. The first and second generations of unit root tests were conducted to ascertain the panel data's cross-section dependence and structural breaks. Inferences drawn from these pre-estimation tests paved the way for unbiased empirical investigations across all the set objectives in the study.

From the empirical literature, this study has discovered the wide disconnections between human capital skills, infrastructural development and industrial sector growth caused by varied factors. For instance, most previous researchers failed to use in-depth determinants of industrial output growth through the three major dimensions: cost, income, and output (Kairo et al., 2017), which were incorporated in this study. Also, this study contributed to the empirical methodology through the following objectives:

To achieve the first objective, this study tries to incorporate different dimensions of determining factors and unify them to account for industrial sector growth through an augmented endogenous growth model. Therefore, the System-GMM was adopted to account for the effects of factors determining industrial output growth in SSA. This technique was incorporated to address the study's possible simultaneity and endogeneity problems.

To achieve the second objective, this study carried out a sub-region comparative analysis of the human capital skills development and infrastructural development effects on industrial output growth to propel proactive and suitable future policy guides across EAC ECASS ECOWAS and SADC. Notably, comparative analysis via the Robust sub-sampling technique and FE-LSDV modelling was used to compare different specific effects of human capital skills development and infrastructural development on industrial sector growth across the sub-regional economic blocs in SSA. Consequently, the effects of individual countries and sub-regional specifics were ascertained. The threshold and asymmetric effects of human capital skills and infrastructure on industrial output growth were identified to achieve the third objective. By so doing, the dual effect of infrastructure and human capital skills was disclosed through panel threshold regression analysis and nonlinear Autoregressive Distributed Lags (NARDL) techniques across sub-regions in SSA. The two regimes' effects paved the way for proper policy direction for industrial sector growth and to know which infrastructure and human capital skills indicators can be prioritised for industrial output growth in SSA.

In summary, this study intends to encompass appropriate sources of human capital skills such as school enrolment, opportunity cost and household consumption. Again, this study intends to establish which appropriate human capital skills and infrastructure indicators with higher returns to scale can be identified to catalyse industrial growth performance in SSA. Consequently, it appears that early writers could not show the causes of poor industrial output growth in SSA despite the large populace and presence of infrastructure, which can be attributed to poor human capital potential and poor infrastructural spread to support the diffusion of knowledge for productive growth. A few studies, like those by Eigbiremolen and Anaduaka (2014), Abur (2014), Mendes et al. (2014), and Thamma-Apiroam (2015), Piabuo and Tieguhong (2017), Bokana and Akinola (2017), Okumoko et al. (2018) and Opoku et al. (2018), Akinola and Mbonigaba (2019), Keji (2021), Mpofu and Nemashakwe (2023) and Odionye and Chukwu (2023) made some efforts through diverse focus and scope with shreds of evidence from either a country case or other regions like Asia, America, etc., with no direct emphasizes on how human capital skills and infrastructural development comparatively affect industrial sector growth in SSA via sub-sample analysis, FE-LSDV and the short-run and long-run two-step system General Methods of Movements (i.e., System-GMM) estimation technique).

2.10 SUMMARY OF CHAPTER TWO

This chapter presented the conceptual frameworks around the concepts of the study. The background theories of the concepts were presented to expand this study's meanings and theoretical applications. The theoretical frameworks are also presented in this chapter. Different theories were linked to the conceptual framework to show how these theories were pertinent to the study. The empirical works of literature were drawn from outside Africa, within Africa and sub-Saharan Africa to ascertain the gaps in the literature. Moreover, these gaps were put into perspective. Hence, the literature discovered a series of gaps, and corrective measures to address these gaps are elaborated in this chapter.

The methodology section is next.

CHAPTER THREE

METHODOLOGY

3.1 INTRODUCTION

This chapter addressed the theoretical modelling for the study's methodology analysis. The chapter worked through panel data sources, data analysis, estimating techniques to be employed, theoretical frameworks that justify these techniques, Justifications for the empirical variables of measurements, a priori expectations of those variables and data analysis.

3.2 DATA SOURCES

All the Data were drawn from secondary sources via the Word Bank Index and World Bank Development indicators (2022). Specifically, data for some of the variables were also sourced based on specialized international agencies such as the International Labour Organisation (ILO), United Nations Educational, Scientific and Cultural Organisation (UNESCO), World Population Prospects database, Apex Banks of the selected countries, index mundi, the global economy, and trading economics data, among others. Data were drawn to estimate all the models specified for sub-Saharan African economies between 1990 and 2022. Consequently, the data sourced were subjected to varied estimating techniques to achieve all the set objectives in the study. The first objective was drawn based on the selected indicators for measurement that explained the determinants of industrial output growth in the SSA. The data for the second objective were disaggregated and panelled to compare the effects of human capital skills and infrastructure on industrial output growth across the sub-regional economic blocs in SSA. Meanwhile, the question related to the third objective was answered through a more expanded data analysis drawn from the individual sub-regional bloc and the SSA as a whole. The intention was to introduce dual effects of the indicators for industrial output growth, which was aimed to ascertain the threshold and asymmetric effects of human capital and infrastructure on industrial sector growth. Therefore, these dual effects of human capital skills and infrastructure indicators on industrial output growth in SSA were disclosed in the short and long run.

3.3 THEORETICAL FRAMEWORK IN THE STUDY

According to Lucas (1988), Rebelo (1991), Mankiw, Romer, and Weil (1992), the pioneers of endogenous output growth theory, posited that production was built on the ability of human capital to impact output growth in the short-run and long-run (Piabuo & Tieguhong, 2017). The implication is that increasing labour skills through quality education alongside high-tech skills in line with a conducive work environment improves output growth. Therefore, Mankiw, Romer, and Weil (1992), endogenously explain the accumulation of human capital indicators and infrastructural inputs as complementarity sources of output growth. Notably, the theoretical models adapted to the study were drawn based on the study's concepts. *Human capital skills* are endogenous. I*nfrastructure input* is partly endogenous and exogenous. In contrast, *industrial output growth,* an explanatory variable and endogenous factor within an economy, was an outcome of the complementarity of the components- human capital skills and infrastructure for general output growth.

The study is attentive to our research concepts that revolved around both endogenous and partly exogenous variables in which appropriate clews were sought from early studies such as Lucas (2002), Kutu and Ngalawa (2016), Hongzhong et al. (2018), Ibrahim (2019), Ogunjobi et al., (2021), Ndombi Ondze (2021), Goulielmos, (2021), Amoah and Jehu-Appiah (2022), Huang, Zeng, Wang, and Zhang (2022), Jiang (2022), Dramani et al., (2023) and Du et al., (2023) by subjecting total output Y to sectorial output y*. Consequently, all the theoretical models were aligned with Rebelo, Mankiw, Romer, and Weil's augmented endogenous model and modified Cobb-Douglas function to empirically explain the first, second, and third objectives, respectively. By extension, further insights into those theoretical models were garnered from early studies like Lucas (2002), Kutu and Ngalawa (2016), Akinola and Bokana (2017), Piabuo and Tieguhong (2017), Oluwatobi and Olurinola (2011), Mbonigaba and Akinola (2019) and Goulielmos (2021) and with necessary modifications. Hence, the generic endogenous model is explicitly expressed as

$$Y = AK^{\alpha}L(h)^{\beta} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (3.1)$$

Where Y= Amount of Output, K=Quantity of physical capital, h=composition of Human Capital, labour as related to working age concerning output; level of Factor Productivity; α = Capital input elasticity in relationship to output Y, while β =Human capital input elasticity in connection to output Y. Consequently, the 3.1 model would be implicitly discussed in line with the objectives of the study. *Note that* $0 < \alpha, \beta < 1, \beta + \alpha < 1$.

3.3.1 Model for the Broad Objective

About the origin of our theoretical framework. Moving ahead, to assess the connection between human capital, infrastructure development, and industrial output growth. We shall inject country focus and the period into the Rebelo, Mankiw, Romer, and Weil augmented model $\{Y = AK^{\alpha}L(h)^{\beta}\}$ to establish the focus and scope of this study. The augmented model of Rebelo, Mankiw, Romer, and Weil is explicitly readjusted and re-modelled in line with Kutu and Ngalawa (2016), Orji, Worika and Umofia (2017) and Ndombi Ondze (2021).

The neoclassical growth model forms the bedrock of the endogenous output growth model, which is explicitly expressed as:

$$Y = Y_{i,t} = f\left(A_{i,t}K_{i,t}, h_{i,t}L_{i,t}\right) \dots \dots \dots \dots \dots \dots \dots \dots \dots \quad 3.1.1$$

Where Y_{it} represents the broad output growth of country i over time t, K_{it} explains the capital stock in country i over time t, and L_{it} denotes labour inputs in country i over time t. h_{it} expresses the endogenous impact of human capital toward industrial output growth in country i over time t. Here, all factor inputs are assumed to have explained the link between investments in human capital and infrastructural development toward industrial sector growth across countries.

"Current theoretical literature on human capital and its influence on firm performance suggest that a strategic approach in human capital enhancement may contribute to organisational success (Mendes, Nunes & Sequeira, 2011)" Therefore, it is pertinent to assess how the roles of human capital skills advancement complement infrastructure development towards improving industrial output growth. Also, the recent campaign against classical cointegrating symmetry models has brought the model asymmetric cointegration modelling between indicators of human capital skills, infrastructure and industrial output growth in SSA (Shin et al., 2014; Tang & Kogid, 2022). Consequently, the asymmetric model disaggregates effects into two regimes on a dependent estimate using a single equation of the partial sum framework model, which makes simultaneous estimation asymmetric possible.

Re-adjusting and transforming model 3.1 to the sector output growth models to suit our research objectives: this study borrowed clews from Lucas (2002), Mendes et al. (2011), Kutu and Ngalawa (2016), Orji, Worika and Umofia (2017), Ndombi Ondze (2021), Goulielmos, (2021). Amoah and Jehu-Appiah (2022), Huang, Zeng, Wang, and Zhang (2022) and Jiang (2022) in disaggregating traditional Y output into y* as sector output to build a pointer model in the study.

For example, we mathematically expand the augmented endogenous output model in 3.1 by incorporating time (t) and country (i) to account for both human capital skills (which is endogenous) and infrastructure (which is partly endogenous and partly exogenous) to become;

$$Y = A_{i,t}{K_{i,t}}^{\alpha}L_{i,t}(h)^{\beta} \ldots 3.1.2$$

By disaggregating and deflating Y to address sectorial output growth. Y is transformed to become y* for industrial sector output growth in terms of "h" as the measure of endogenous human capital skills and K as the measure of physical capital such as infrastructure; when *AL* is divided Y, L is assumed to have constant returns to scale. Hence, the power of L becomes one (1) at this stage to account for only endogenous skill returns of human capital in h thus;

$$Y = AK^{\alpha}h^{\beta}L = ALK^{\alpha}h^{\beta} \ldots 3.1.3$$

Hence, Y is transformed from its generic form to its specific (sector) form to capture sectorial output growth, i.e. actual industrial sector growth.

$$\frac{Y}{AL} = k^{\alpha}h^{\beta} = y* = k^{\alpha}h^{\beta} \ldots 3.1.4$$

Where y* is sectorial output growth in terms of human capital skills (h) and physical infrastructure (k) with the assumption that AL denotes the initial internal technical efficiency (aligning with Jiang (2022) on the importance of internal influence and induce coefficients as a source of industrial Output growth) and Labour force composition outside the industrial sector. They were used to deflate aggregate output level (Y) across sectors.

Hence, the pointer model is **y* =** $\boldsymbol{K^{\alpha}h^{\beta}}$ ………………….3.1.5

Model 3.1.5 is used to express the interaction between human capital skills (h), infrastructural (K) and y*, which is the real sectorial output (proxy as industrial sector output). They are aligning with

Kutu and Ngalawa (2016), Hongzhong, Hossain, and Sultanuzzaman (2018), Amoah and Jehu-Appiah (2022), Nkemgha Nchofoung and Sundjo (2022) and Bouattour, Kalai and Helali (2024) on the determinant of industrial output.

3.3.2 Models for the First Objective

The specified models in this section were built to estimate the determinants of industrial output growth across the SSA region, which is the study's first objective.

The study's first objective is to examine the determinants of industrial output growth. Based on this objective, certain pre-estimations were carried out to unravel true measures of the key factors emanating from human capital skills and infrastructure. Consequently, sub-sample analysis was adopted to reveal the true determinants of human capital skills and infrastructure across SSA.
Consequently, the extant endogenous growth theory was adopted in the study to ascertain the determinants of industrial output growth via both human capital and physical capital before estimating their comparative effects on industrial output growth, which is the first objective. This pre-objective study aims to see the strength of human capital skills and physical capital across SSA. As advocated by Arrow (1962) and Lucas (1988), Romer (1994) emphasised different determinants of output growth via human capital and Physical capital and how sustainable these investments in both human capital and physical capital can propel output growth. Therefore, Mankiw et al. (1992) and Romer (1994) introduced stock knowledge in human capital as the public stock for general output growth.

Models Accounting for Human Capital Skills determinants when other factors are assumed to be constant:

The aim of this model in the study is to account for the strength of the determinants of industrial output through measures of human capital skills and physical capital across SSA. As advocated by Arrow (1962) and Lucas (1988), Romer (1994) emphasised different determinants of output growth via human capital and Physical capital and how sustainable investments in both human capital and physical capital can propel output growth. Mankiw et al., (1992) and Romer (1994), therefore, introduced stock knowledge in human capital as the public stock for general output growth to come:

$$y*_j = A(h)F(k_J, h_j)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..3.2.1$$

Therefore, model 3.2.1 is transformed to explicit model and Log-linearize for econometric analysis; $logy*_j = logA + logh + logk_j +, logh_j + U\ldots\ldots\ldots$3.2.2

This is to address likelihood of extremely high and ambiguous dataset to avoid the computational complexity for empirical derivations in the cause of the analysis, especially in achieving linearity of the estimates (Zietz, 2008; Bellemare & Wichman, 2020).

Where y* implies industrial sector output, h denotes the aggregate stock of human capital. A explains factor intensity, k j means the stock of physical capital across country j, hj implies public stock of human capital in j. j describes individual SSA countries, and U explains the stochastic error terms in the model. So, publicness in H and H j is different in model 3.2.2. Therefore, the transition from model 3.2.1 to 3.2.2 improved the modelling structure and avoided possible spurious econometric output. Consequently, ambiguous values within the measurement variables were logged.

Readjusting model 3.2.2 for objective one, it is assumed that countries can control factor inputs in the production process as rival inputs without disrupting output growth. Therefore let

$$y*_j = y*_{it},\ k_j = k_{it}, h = h_j = h_{it}, and\ U_{it}\ldots\ldots\ldots\ldots\ldots\ldots\ldots..3.2.3$$

Where i and t represent cross-country specifics and time trends, h_{it} implies aggregate stock of human capital across sub-regions in SSA. K_{it} aggregate stock of infrastructure or aggregates stock of physical capital across sub-regions in SSA. Hence, model 3.2.2 becomes;

$$logy*_{it} = logA_{it} + log\boldsymbol{k_{it}} + log\boldsymbol{h_{it}} + U_{it}\ldots\ldots\ldots\ldots3.2.4$$

Notably, model 3.2.4 was motivated to address problems arising from the empirical analysis in a knowledge-based economy that allows diffusion of knowledge and technology (Lucas, 1988; Mankiw et al., 1992; Romer, 1994; Bokana & Akinola, 2017). Hence, the industrial output determinants model evaluates factors determining industrial output growth via the trend analysis and the two-step system GMM across SSA.

Alternatively, to further expand model 3.2.4 to account for physical capital or infrastructure determinants to achieve the rest of the first specific objective.

Background views and justifications were drawn to align the pointer model 3.1.5 with other proponents of endogenous output growth models. Hence, perspectives drawn from Lucas (1988) by reviewing other related arguments of the endogenous nature of human capital skills, Lucas's (1988) Postulations: From a related model of Lucas, it was argued that the 3.1.1 model depicts the constant return to scale function hL, where it is assumed that the additional product of capital is constant. The aggregation of (K) determines Y, and A is a position integer, and the AK model is derived from the 3.1 *s*ince AK theory explains that the long-run output growth rate is determined by its rate of savings (Makaula, 2014). This means that when a fixed portion of s of productivity is saved, then the fixed rate of depreciation α exists, with the rate turning to net investment as:

$$\frac{dK}{dt} = sY - \alpha K \ldots .3.2.5$$

This means that the output rate is stated as:

$$g = \frac{1Yd}{Ydt} = \frac{1Kd}{Kdt} = sA - \alpha \ldots .3.2.6$$

Therefore, as the rate of savings rises, output growth and relatively industrial output growth constantly increase. Here, Lucas argued that the accumulation of human capital and physical capital caused output growth; as a result, productive growth hitherto becomes endogenous.

$$Y = AK^{\alpha}L(uh)^{1-\alpha} \ldots \ldots . .3.2.7$$

$\text{the partial derivative takes away } L \text{ using the product rule i.e.} \triangle \frac{Y}{\triangle L}$. Hence, re-write as

$$y = AK\alpha(uh)1 - \alpha \ldots .3.2.8$$

That is, the production function of constant return to scale is k and uh. Accumulation of capital k along with uh proceeds through the mathematical difference equation; hence,

$$K = y - c - (\xi + \dot{\alpha})k \ldots \ldots \ldots \ldots .3.2.9$$

Therefore, h accumulation continues through common derivatives of the function thus;

$$\ddot{h} = \phi h(1 - L) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots .3.2.10$$

$$\frac{\partial \ddot{\mathrm{h}}}{\partial h} = \phi(1 - L) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots 3.2.11$$

On this note, ϕ slope of the accumulated stock of differences in a portion of active working age and supposed working ages, ∂ḧ/∂h is the difference in combined human capital stocks to accumulated human capital output, *L* is regarded as the fragment at which labour is engaged in productive ventures, while 1-*L* supposed to be working, as the percentage at which accumulation and production of knowledge are displayed. According to Lucas, in between the two assertions, human capital accumulation is found.

Based on the analogy drawn from different perspectives that justified the adoption of endogenous models in the study, we must align with Lucas, Mankiw, Romer, and Weil's models to achieve our objective one and the rest of the set objectives in the study. These models explain the sources of knowledge and innovation as causal of output growth, which emphasises cumulative investment as an expanded form of the Lucas model, hence pertinent for cross-country industrial sector growth (Kutu & Ngalawa, 2016; Orji, Worika & Umofia, 2017; Ndombi Ondze, 2021; Amoah & Jehu-Appiah, 2022; & Jiang, 2022, Keji, Akinola & Mbonigaba, 2024). The models were compressed and expressed as pointers thus;

$$\boldsymbol{y*} = \boldsymbol{k}^{\alpha}\boldsymbol{h}^{\beta} \dots\dots\dots\dots\dots\dots\dots 3.2.12$$

Model 3.2.12 is used to express the interaction between human capital skills (h) [being an endogenous factor], infrastructural (k) [as physical capital that accounts for infrastructure] and sectorial output (proxy as industrial sector output) (y*) [being disaggregated output across all firms].

Drawing another perspective by accounting for the true coefficients of the estimates in model 3.2.12 via partial derivatives of the factor determinants for econometric analysis of each of the key determining factor inputs thus:

Where,

$$h_{i,t} = \left[\frac{y*_{i,t}}{K_{i,t}{}^{\alpha}}\right]^{-\beta} = \left(y*_{i,t}\right)^{-\beta}(K_{i,t})^{-\alpha} \dots\dots\dots\dots 3.2.13$$

Model 3.2.12 can be log linearized as: $h_{i,t} = -\beta log y*_{i,t} - \alpha log K_{i,t}$ …….3.2.14

Making human capital estimates become independent variables through the expansion of model 3.8 as;

$$-\beta logy *_{i,t} = -h_{i,t} - \alpha logK_{i,t} \ldots\ldots\ldots\ldots.. 3.2.15$$

Divide through by -1 and expand the function to have;

$$logy *_{i,t} = h/\beta_{i,t} + \alpha logK/\beta_{i,t} \ldots\ldots\ldots\ldots\ldots\ldots\ 3.2.16$$

Let $h/\beta_{i,t} = \frac{1}{\beta}h = \Phi h, where\ \Phi = \frac{1}{\beta};$

Therefore, model 3.2.16 becomes $logy *_{i,t} = \Phi h_{i,t} + \alpha logK/\beta_{i,t} = \Phi h_{i,t} + \frac{\alpha}{\beta} logk_{i,t} \ldots$ 3.2.17

$$and\ \frac{\alpha}{\beta} = \gamma$$

Consequently, model 3.2.12 is hereby logged linearized to becomes

$$\boldsymbol{logy *_{i,t} = \Phi h_{i,t} + \gamma logk_{i,t} \ldots\ 3.2.18}$$

And further expanded to suit econometric analysis through the inclusion of constant terms thus;

Model 3.2.18 becomes $\boldsymbol{logy *_{i,t} = a_{i,t} + \Phi h_{i,t} + \gamma logk_{i,t} \ldots\ 3.2.19}$

Model 3.2.19 expressed human capital skill and infrastructure as causal of industrial output (y*) function. Moreover, to achieve our main first specific objective, human capital skill is proxy as h subscripts (i,t), infrastructure is proxy as k subscripts (i,t) and industrial output is expressed as y* subscript (i,t) (i.e. human capital is determined from the output dimension) to supply along infrastructure and consumption of human capital efforts across the selected countries were being accounted for. U subscript (i,t) explains other stochastic factors determining human capital, Φ and γ symbolize slopes of the factor estimates and 'a' signals the constant. k subscript (i,t) is further expanded along with additional key and control factors such as cost of infrastructure, education, public funding for health, school enrolment, exchange rate, access to transport, access to energy, ICT, inflation rate, average time spent in school (which account for an opportunity as part of cost dimension). Also, education outcomes, health outcomes, literacy rate, labour participation rate, and life expectancy contribute to SSA's human capital dynamics, which denotes the constant terms.

3.3.3 Models for the Second Objective

The specified models in this section were built to estimate the measures of comparative effects of human capital skill development and infrastructural development on industrial sector growth across the regional economic blocs in Sub-Saharan African economies. The study's second objective is to investigate and compare how comparative effects of human capital skill development and infrastructural development affect industrial sector growth across the regional economic blocs in Sub-Saharan Africa. Leveraging equation 3.9iv above, we can re-specify the augmented output growth model in a linear log form to accommodate only key measures of human capital skills along the key infrastructure measures. Notably, K measures the amount of physical capital, such as infrastructure, and h explains total human capital skills for attaining industrial sector growth (Ndombi Ondze, 2021; Amoah & Jehu-Appiah, 2022; Keji, Akinola & Mbonigaba, 2024). Rebelo further argued for balancing physical and human capital (i.e., human capital-technology). Therefore, model 3.2.19 is mathematically expanded to accommodate the comparative effects of human capital skill and infrastructure techs, all things being equal.

Model 3.2.19 under the first objective was linked to the second objective, and it was re-specified for slight adjustment to become $\boldsymbol{logy}*_{\boldsymbol{i,t}}= \boldsymbol{a}_{\boldsymbol{i,t}} + \boldsymbol{\Phi h}_{\boldsymbol{i,t}} + \boldsymbol{\gamma logk}_{\boldsymbol{i,t}} \ldots\ \mathbf{3.3.0}$ to begin the modelling for the second objective.

Expanding model 3.3.0 by introducing key and control variables for h and k to become 3.3.1

$$\boldsymbol{logy}*_{\boldsymbol{i,t}}= \boldsymbol{a}_{\boldsymbol{i,t}} + \boldsymbol{\Phi h}_{\boldsymbol{i,t}} + \boldsymbol{\gamma logk}_{\boldsymbol{i,t}} + \alpha_1\boldsymbol{AYS} + \boldsymbol{\alpha}_2\boldsymbol{HOC} + \alpha_3\boldsymbol{GCF} + \alpha_4\boldsymbol{FDI} \ldots\ \mathbf{3.3.1}$$

Where AYS signifies average years of schooling and HOC means household consumption as direct control factors of h. While GCF explains gross capital formation (such as domestic capital formation) in physical infrastructure, FDI denotes foreign direct investment as a direct control variable of k regarding investment in physical infrastructure (foreign investors in infrastructure or capital goods). Time and country i, t are injected into model 3.10;

$$\boldsymbol{logy}*_{\boldsymbol{i,t}}= \boldsymbol{a}_{\boldsymbol{i,t}} + \boldsymbol{\Phi h}_{\boldsymbol{i,t}} + \boldsymbol{\gamma logK}_{\boldsymbol{i,t}} + \alpha_1\boldsymbol{AYS}_{\boldsymbol{i,t}} + \boldsymbol{\alpha}_2\boldsymbol{HOC}_{\boldsymbol{i,t}} + \alpha_3\boldsymbol{GCF}_{\boldsymbol{i,t}} + \alpha_4\boldsymbol{FDI}_{\boldsymbol{i,t}} \ldots\ \mathbf{3.3.2}$$

Through further expansion with the stochastic term, model 3.3.2 becomes;

$$\boldsymbol{logy}*_{i,t}= \boldsymbol{a}_{i,t} + \boldsymbol{\Phi h}_{i,t} + \boldsymbol{\gamma logK}_{i,t} + \alpha_1\boldsymbol{AYS}_{i,t} + \boldsymbol{\alpha}_2\boldsymbol{HOC}_{i,t} + \alpha_3\boldsymbol{GCF}_{i,t} + \alpha_4\boldsymbol{FDI}_{i,t} + \boldsymbol{U}_{i,t} \dots \mathbf{3.3.3}$$

Based on the second objective, k and h will be compared with other control variables to become model 3.3.3 interactively. This is the model for objective two.

Where the combined comparative effects of human capital (h) are evaluated side by side with the infrastructural development (log k) on industrial sector growth (log y*) in SSA.

Again, expanding further by leveraging on the second objective, comparing the effects of human capital h to the effects of infrastructure k in models 3.3.3 is pertinent. Partial derivatives of 3.3.3 were carried out to account for how the individual key variables of interest that predicted industrial output growth across sub-regional blocs, all things being equal thus;

$$\frac{\Delta y*}{\Delta h} = \Delta logy*/\Delta h = \boldsymbol{\Phi}_{i,t} + \boldsymbol{\gamma logk}_{i,t} + \alpha_1\boldsymbol{AYS}_{i,t} + \boldsymbol{\alpha}_2\boldsymbol{HOC}_{i,t} + \alpha_3\boldsymbol{GCF}_{i,t} + \alpha_4\boldsymbol{FDI}_{i,t} + \boldsymbol{U}_{i,t} \dots \mathbf{3.3.4}$$

Normalizing model 3.3.4 according to the law of logarithm to account for the only change in human capital (h) effects on industrial output growth, all things being equal thus;

$$\Delta logy*/\Delta h = \boldsymbol{\Phi}_{i,t} + \boldsymbol{\gamma logk}_{i,t} + \alpha_1\boldsymbol{AYS}_{i,t} + \boldsymbol{\alpha}_2\boldsymbol{HOC}_{i,t} + \alpha_3\boldsymbol{GCF}_{i,t} + \alpha_4\boldsymbol{FDI}_{i,t} + \boldsymbol{U}_{i,t} \dots \mathbf{3.3.5}$$

Also, to estimate the change of effects in infrastructural (k) development on industrial output growth, partial derivation of y* concerning k is carried out in model 3.3.3 by applying logarithm formulae, all equal.

$$\frac{\Delta y*}{\Delta k} = \frac{\Delta logy*}{\Delta k} = \boldsymbol{\Phi h}_{i,t} + \boldsymbol{\gamma logk}^{\gamma-\mathbf{1}}(\boldsymbol{logk}^{\gamma})_{i,t} + \alpha_1\boldsymbol{AYS}_{i,t} + \boldsymbol{\alpha}_2\boldsymbol{HOC}_{i,t} + \alpha_3\boldsymbol{GCF}_{i,t} + \alpha_4\boldsymbol{FDI}_{i,t} + \boldsymbol{U}_{i,t} \dots\dots \mathbf{3.3.6}$$

Normalizing model 3.3.6 according to the law of logarithm to get change in infrastructure (K) effects on industrial output growth thus;

$$\frac{\Delta logy*}{\Delta k} = \boldsymbol{\Phi h}_{i,t} + \boldsymbol{\gamma}(\boldsymbol{\gamma}-\mathbf{1})\boldsymbol{logK}(\boldsymbol{logk}^{\gamma})_{i,t} + \alpha_1\boldsymbol{AYS}_{i,t} + \boldsymbol{\alpha}_2\boldsymbol{HOC}_{i,t} + \alpha_3\boldsymbol{GCF}_{i,t} + \alpha_4\boldsymbol{FDI}_{i,t} + \boldsymbol{U}_{i,t} \dots\dots \mathbf{3.3.7}$$

Models 3.14 and 3.3.7 express the individual effects of the two key human capital and infrastructure variables across ECA ECCAS ECOWAS and SADC, respectively, mainly when either of the factors is held constant. This shows that human capital and infrastructure comparatively affect industrial output growth in SSA.

3.3.4 Models for the Third Objective

The specified models in this section were built to estimate the threshold and asymmetric effects of human capital skill development and infrastructural development on industrial output growth across sub-regional economic blocs in Sub-Saharan Africa. This third specific objective of the study assessed how certain threshold trajectories can be set for industrial output growth and its asymmetric effects on industrial output growth via human capital and infrastructural development across sub-regional economies in SSA. Nonlinear autoregressive Distributed Lags models were used to estimate nonlinear (Asymmetric) inter-relationships among variables. This objective is pertinent to this study because it allows us to assess how two effects regimes predicted industrial output growth. Also, the paired effects from the two key variables were ranked in case of sudden disruption in the model, which can influence industrial output growth through investment decisions in human capital skills and infrastructure across sub-regional blocs in SSA. The conditions for adopting non-linear ARDL models guided our choice of empirical model building in the study.

3.3.4.1 The Justifications for Modelling Process of Threshold Regression

In this study, necessary clews were from Hansen (2011), Shin (2016), Ndoricimpa (2017), Seo et al. (2019), Nkemgha et al. (2022), Odionye and Chukwu (2023), Du et al., (2023), Woldu and Kanó, (2023), Dramani et al., (2023), and Bouattour et al., (2024) in adopting threshold regression model to examine the threshold effect of human capital skill development and infrastructural development on industrial output growth across Sub-Saharan Africa. It is pertinent to capture the nonlinear dynamics between human capital skills infrastructural and industrial output growth. This model was chosen over linear models due to the restrictive nature of linear models with the inability to capture parsimoniously asymmetric effects, which accounted for nonlinear dynamics (Woldu & Kanó, 2023). Therefore, the single threshold regression model was modelled thus:

$$Y_t = \theta_1 X_t + U_t \quad q_t \leq \gamma \qquad 3.4.1$$

$$Y_t = \theta_2 X_t + U_t \quad q_t > \gamma \qquad 3.4.2$$

Where $\boldsymbol{Y_t}$ signifies the dependent variable, $\boldsymbol{X_t}$ denotes the independent variable, $\boldsymbol{q_t}$ explained the threshold variable, $\boldsymbol{\gamma}$ accounts for the threshold intensity (quantity), and $\boldsymbol{U_t}$ denotes the stochastic term. The single threshold regression model is (3.4.1), when$\boldsymbol{q_t} \leq \boldsymbol{\gamma}$. Furthermore, the single threshold regression model is (3.4.2) when$\boldsymbol{q_t} > \boldsymbol{\gamma}$. The indicative function for human capital skills $I(\boldsymbol{HCS_t} \leq \boldsymbol{\gamma_1})$ is then built. The indicative function for infrastructure $I(\boldsymbol{INF_t} \leq \boldsymbol{\gamma_1})$ is then built. Therefore, if the conditions in parentheses were met, the value is 1; otherwise, it is 0. Merging the above two formulas brought the following:

$$\Delta logIDO_{it} = \theta_1 HCS_{it}\mathrm{I}(HCS_{it} \leq \gamma_1) + \theta_2 HCS_t\mathrm{I}(\gamma_1 < HCS_t < \gamma_2) + \theta_3 HCS_t\mathrm{I}(\gamma_1 > HCS_t) + aw_t + U_t \qquad 3.4.3$$

$$\Delta logIDO_t = \theta_1 INF_t\mathrm{I}(INF_t \leq \gamma_1) + \theta_2 INF_t\mathrm{I}(\gamma_1 < INF_t < \gamma_2) + \theta_3 INF_t\mathrm{I}(\gamma_1 > HCS_t) + aw_t + U_t \qquad 3.4.4$$

Where $\gamma_1 and\ \gamma_2$ denote respective threshold coefficients, and θs explains coefficients of the slope. I (.) is the indicator function. ΔlogIDO explains the industrial output growth, which is denoted as the dependent variable at time t=1, 2, HCSIDO measures the human capital skills-to-industrial output, and INFIDO measures the infrastructure-to-industrial output, which are classified as regime-regressor indicators. w explains the control variables that consist of the gross capital formation-to-industrial output growth and foreign direct investment-to-industrial output growth. U denotes the stochastic error term. The endogenous variable is the industrial output growth. The study focuses on human capital skills-to-industrial output (HCSIDO) and infrastructure-to-industrial output (INFIDO). This is because HCSIDO and INFIDO can be attributed to direct factors influencing industrial output growth. Also, other factors were well controlled in the modelling process.

Consequently, the model was carried out in three sequential tests. Firstly, the test for the null hypothesis of no threshold was examined. Secondly, the test for the null hypothesis of both no thresholds was examined. Thirdly, the single threshold was tested. This study adopted human capital-industrial output growth (HID) and infrastructure-industrial output growth (IID) as threshold variables to ascertain the threshold effect on industrial output growth. Two tests were then estimated. The first was the significance test of the threshold effect, and the second was to determine whether the threshold estimated value equals the true value. Also, the bootstrap method was used to build the P value to test for the threshold significance effect. The $LR = -2ln\ (1 - \sqrt{1-\propto})$ of the likelihood ratio (LR) statistic was used to test the consistency of the threshold value, and the confidence interval of the estimated threshold value was achieved (Hansen, 2000; Bouattour et al., 2024). Analysing the linearity (LR) test would establish whether there is a non-linear link between human capital, infrastructure and industrial output growth. Therefore, the hypothesis of no threshold can be rejected. Testing the double threshold effect, the first threshold is expected to be recognised.

Moreover, the first threshold value must be proven when the second threshold exists. In line with Hansen and Seo, Kim and Kim, the first and the second threshold estimated value is ascertained, and then the first threshold estimation value is established with the minimum sum of squared residuals. Hence, the significance and validity of the double threshold effect are then determined. Notably, when all these tests are conceded, the highlighted process is repeated to further estimate the three threshold effects.

3.3.4.1.1 The Justifications for the Modelling Process of Non-Linear Autoregressive Distributed Lags (NARDL)

The linear autoregressive distributed lags (ARDL) model can measure the short-run and long-run estimates to reveal symmetric connections among the estimating series. However, it is ineffective in ascertaining the asymmetric effect among the estimated variables (Shin & Greenwood-Nimmo, 2014). The asymmetric effect is pertinent in the study because it captures the effects of expected two regimes among the estimation variable. Notably, the Non-Linear Autoregressive Distributed Lags (NARDL) model suites the third objective in the study because it captures concurrent estimation of short- and long-term asymmetry effects compared to the ARDL model. Hence, this justifies considering the NARDL model over the ARDL model in the study. In the primary time, the NARDL models were decomposed into generic and harmonised formulations for reliable econometric analysis. It is worth noting that integrating all variables in the same order is not mandatory using the NARDL model (Shin et al., 2023). Drawing clews from Shin, Yu, Greenwood-Nimmo (2014), Sama et al. (2023) and Noha and Daniela (2024), the NARDL model is specified thus;

By leveraging on the pointer model and re-adjusting model 3.11 to become 3.4.5;

$$\boldsymbol{logy *_{i,t}= a_{i,t} + \Phi h_{i,t} + \gamma logK_{i,t}} + \alpha_1 \boldsymbol{AYS_{i,t}} + \boldsymbol{\alpha_2 HOC_{i,t}} + \alpha_3 \boldsymbol{GCF_{i,t}} + \alpha_4 \boldsymbol{FDI_{i,t}} + \boldsymbol{U_{i,t}} \dots \mathbf{3.4.5}$$

Under this condition, the composition and measures of human capital skill **(h)** and infrastructure **(k),** along with the control variables, were elaborated. The coefficient estimates were harmonised as β where y becomes IDO (Industrial Output Growth), human capital skills **h** captures data from [School enrolment rate (SER), Literacy rate (LIR), Labour Participation rate (LPR), and Labour force (LBF)], infrastructure **k** captures data from [Access to Transportation (ACT), Access to Energy (ACE), Access to Water Resources (AWP) and Information Technology (ICT)]. At the same time, the control variables are Gross Capital Formation (GCF) and Foreign Direct Investment (FDI). For the harmonised formulations, the human capital skills indicators were denoted as HCSD, while infrastructure indicators were captured as INF for simplistic forms of modelling.

$$logIDO_{i,t} = \beta_0 + \beta^{-} logGCF^{-}{}_{i,t} + \beta^{+}\log FDI^{+}{}_{i,t} + \beta\left[logSER_{i,t} + logLIR_{i,t} + logLPR_{i,t} + logLBF_{i,t}\right] + \beta\left[logACT_{i,t} + logACE_{i,t} + logICT_{i,t} + logAWP_{i,t}\right] + +u_{i,t} \dots\dots..3.4.6i$$

OR

Harmonised as:

$$logIDO_{i,t} = \beta_0 + \beta^{-} logGCF^{-}{}_{i,t} + \beta^{+}\log FDI^{+}{}_{i,t} + \beta\left[logHCSD_{i,t}\right] + \beta\left[logINF_{i,t}\right] + +u_{i,t} \dots\dots..3.4.6ii$$

Note: the model 3.4.6i was harmonised to model 3.4.6ii to address possible computional complexity. Also, the harmonised to models were meant to address sub-regional specifics by disclosing individual indicators for empirical analysis.

Where, $^{-}$ & $^{+}$ were used to explain the positive and negative partial sums of individual independent variables or the possible effects of different regimes in the NARDL models. Given this, the positive and negative partial sums of the key variables of human capital skills and infrastructure must be elaborated by expanding 3.4.5 further thus;

$$logIDO_{i,t} = \beta_0 + \beta_1{}^{-} logGCF^{-}{}_{i,t} + \beta_2{}^{+}\log FDI^{+}{}_{i,t} + \beta_3{}^{-} SER^{-}{}_{i,t} + \beta_4{}^{+} LIR^{+}{}_{i,t} + \beta_5{}^{-} logLPR^{-}{}_{i,t} + \beta_6{}^{+} logLBF^{+}{}_{i,t} + \beta^{-} logACE^{-}{}_{i,t} + \beta^{+} logACT^{+}{}_{i,t} + \beta^{-} logICT^{-}{}_{i,t} + \beta^{+} logAWP^{-}{}_{i,t} + u_{i,t} \dots..3.4.6iii$$

OR

Harmonised as:

$$logIDO_{i,t} = \beta_0 + \beta_1^{-} logGCF^{-}{}_{i,t} + \beta_2^{+} \log FDI^{+}{}_{i,t} + \beta_3^{-} HCSD^{-}{}_{i,t} + \beta_4^{+} INF^{+}{}_{i,t} + u_{i,t} \ldots .3.4.6iv$$

Please note: the model 3.4.6iii was harmonised to model 3.4.6iv to address possible computional complexity. Also, models 3.4.6i, ii, iii and iv were presented to disclose how individual indicators was partially derived for econometric analysis.

It is important to correctly identify the general true value of each estimate for econometric analysis by disclosing their order of true identity as coefficient elasticity β_0, β_1, β_2………… βn. Therefore, the expected coefficient estimates of FDI, ACE, ACT, LBF, LIR, SER, LPR and GCF in model 3.4.7, 3.48... 3.4.16 were explicitly expressed to explain the asymmetric impact of human capital and infrastructure on industrial output growth. These models were specified to address computational complexity which was based on extant econometric rules (Shin, Yu, Greenwood-Nimmo, 2014; Shin et al., 2023; Seo et al. 2019; Sama et al. 2023; Noha and Daniela, 2024),

$$logGCF^{+}{}_{i,t} = \sum_{j=1}^{p} \triangle\, logGCF^{+}{}_{i,t} = \sum_{j=1}^{p} max\big(\triangle\, logGCF_{i,t}, 0\big),$$

$$logGCF^{-}{}_{i,t} = \sum_{j=1}^{p} \triangle\, logGCF^{-}{}_{i,t} = \sum_{j=1}^{p} min(\triangle\, logGCF_{i,t}, 0) \ldots \ldots \ldots 3.4.7$$

Where $\triangle\, logGCF^{+}{}_{i,t}$ and $\triangle\, logGCF^{-}{}_{i,t}$ denote the increase and decrease in GCF. p is the optimal lag. Notably, model 3.4.7 explicitly meant to reveal the dual effects of domestic investment on industrial sector growth through the indicator for gross capitl formation (GCF).

$$logFDI^{+}{}_{i,t} = \sum_{j=1}^{p} \triangle\, logFDI^{+}{}_{i,t} = \sum_{j=1}^{p} max\big(\triangle\, logFDI_{i,t}, 0\big),$$

$$logFDI^{-}{}_{i,t} = \sum_{j=1}^{p} \triangle\, logFDI^{-}{}_{i,t} = \sum_{j=1}^{p} min(\triangle\, logFDI_{i,t}, 0) \ldots \ldots \ldots 3.4.8$$

Where $\triangle\, logFDI^{+}{}_{i,t}$ and $\triangle\, logFDI^{-}{}_{i,t}$ denote the increase and decrease in FDI. Notably, model 3.4.8 explicitly meant to reveal the dual effects of foriegn direct investment on industrial sector growth through the indicator for foriegn direct investment (FDI).

$$logSER^{+}{}_{i,t} = \sum_{j=1}^{p} \triangle\, logSER^{+}{}_{i,t} = \sum_{j=1}^{p} max(\triangle\, logSER_{i,t}, 0),$$

$$logSER^{-}{}_{i,t} = \sum_{j=1}^{p} \triangle\, logSER^{-}{}_{i,t} = \sum_{j=1}^{p} min(\triangle\, logSER_{i,t}, 0) \ldots\ldots\ldots 3.4.9$$

Where $\triangle\, logSER^{+}{}_{i,t}$ and $\triangle\, logSER^{-}{}_{i,t}$ denote the increase and decrease in SER. Notably, model 3.4.9 explicitly meant to reveal the dual effects of human capital skills on industrial sector growth through the indicator for school enrolment rate (SER).

$$logLIR^{+}{}_{i,t} = \sum_{j=1}^{p} \triangle\, logLIR^{+}{}_{i,t} = \sum_{j=1}^{p} max(\triangle\, logLIR_{i,t}, 0),$$

$$logLIR^{-}{}_{i,t} = \sum_{j=1}^{p} \triangle\, logLIR^{-}{}_{i,t} = \sum_{j=1}^{p} min(\triangle\, logLIR_{i,t}, 0) \ldots\ldots\ldots 3.4.10$$

Where $\triangle\, logLIR^{+}{}_{i,t}$ and $\triangle\, logLIR^{-}{}_{i,t}$ denote the increase and decrease in LIR. Notably, model 3.4.10 explicitly meant to reveal the dual effects of human capital skills on industrial sector growth through the indicator for literacy rate (LIR).

$$logLPR^{+}{}_{i,t} = \sum_{j=1}^{p} \triangle\, logLPR^{+}{}_{i,t} = \sum_{j=1}^{p} max(\triangle\, logLPR_{i,t}, 0),$$

$$logLPR^{-}{}_{i,t} = \sum_{j=1}^{p} \triangle\, logLPR^{-}{}_{i,t} = \sum_{j=1}^{p} min(\triangle\, logLPR_{i,t}, 0) \ldots\ldots\ldots 3.4.11$$

Where $\triangle\, logLPR^{+}{}_{i,t}$ and $\triangle\, logLPR^{-}{}_{i,t}$ denote the increase and decrease in LPR. Notably, model 3.4.11 explicitly meant to reveal the dual effects of human capital skills on industrial sector growth through the indicator for labour participation rate (LPR).

$$logLBF^{+}{}_{i,t} = \sum_{j=1}^{p} \triangle\, logLBF^{+}{}_{i,t} = \sum_{j=1}^{p} max(\triangle\, logLBF_{i,t}, 0),$$

$$logLBF^{-}_{i,t} = \sum_{j=1}^{p} \triangle logLBF^{-}_{i,t} = \sum_{j=1}^{p} min(\triangle logLBF_{i,t}, 0) \dots \dots \dots 3.4.12$$

Where $\triangle logLBF^{+}_{i,t}$ and $\triangle logLBF^{-}_{i,t}$ denote the increase and decrease in LBF. . Notably, model 3.4.12 explicitly meant to reveal the dual effects of human capital skills on industrial sector growth through the indicator for labour force (LBF).

$$logACE^{+}_{i,t} = \sum_{j=1}^{p} \triangle logACE^{+}_{i,t} = \sum_{j=1}^{p} max\left(\triangle logACE_{i,t}, 0\right),$$

$$logACE^{-}_{i,t} = \sum_{j=1}^{p} \triangle logACE^{-}_{i,t} = \sum_{j=1}^{p} min(\triangle logACE_{i,t}, 0) \dots \dots \dots 3.4.13$$

Where $\triangle logACE^{+}_{i,t}$ and $\triangle logACE^{-}_{i,t}$ denote the increase and decrease in ACE. Notably, model 3.4.13 explicitly meant to reveal the dual effects of infrastructure development on industrial sector growth through the indicator for access to energy (ACE).

$$logACT^{+}_{i,t} = \sum_{j=1}^{p} \triangle logACT^{+}_{i,t} = \sum_{j=1}^{p} max\left(\triangle logACT_{i,t}, 0\right),$$

$$logACT^{-}_{i,t} = \sum_{j=1}^{p} \triangle logACT^{-}_{i,t} = \sum_{j=1}^{p} min(\triangle logACT_{i,t}, 0) \dots \dots \dots 3.4.14$$

Where $\triangle logACT^{+}_{i,t}$ and $\triangle logACT^{-}_{i,t}$ denote the increase and decrease in ACT. Notably, model 3.4.14 explicitly meant to reveal the dual effects of infrastructure development on industrial sector growth through the indicator for access to transportation network (ACT).

$$logICT^{+}_{i,t} = \sum_{j=1}^{p} \triangle logICT^{+}_{i,t} = \sum_{j=1}^{p} max\left(\triangle logICT_{i,t}, 0\right),$$

$$logICT^{-}_{i,t} = \sum_{j=1}^{p} \triangle logICT^{-}_{i,t} = \sum_{j=1}^{p} min(\triangle logICT_{i,t}, 0) \dots \dots \dots 3.4.15$$

Where $\triangle\, logICT^{+}{}_{i,t}$ and $\triangle\, logICT^{-}{}_{i,t}$ denote the increase and decrease in ICT. Notably, model 3.4.15 explicitly meant to reveal the dual effects of infrastructure development on industrial sector growth through the indicator for information technology (ICT).

$$logAWP_{i,t} = \sum_{j=1}^{p} \triangle\, logAWP^{+}{}_{i,t} = \sum_{j=1}^{p} max\left(\triangle\, logAWP_{i,t}, 0\right),$$

$$logAWP^{-}{}_{i,t} = \sum_{j=1}^{p} \triangle\, logAWP^{-}{}_{i,t} = \sum_{j=1}^{p} min(\triangle\, logAWP_{i,t}, 0) \ldots \ldots \ldots 3.4.16$$

Where $\triangle\, logAWP^{+}{}_{i,t}$ and $\triangle\, logAWP^{-}{}_{i,t}$ denote the increase and decrease in AWP. Notably, model 3.4.16 explicitly meant to reveal the dual effects of infrastructure development on industrial sector growth through the indicator for access to water resources (AWP).

Harmonising panel and improving model 3.4.6 for sub-regional specifics analysis thus;

$$logIDO_{i,t} = \beta_0 + \beta_1^{-} logGCF^{-}{}_{i,t} + \beta_2^{+}\mathrm{log}FDI^{+}{}_{i,t} + \beta_3^{-}HCSD^{-}{}_{i,t} + \beta_4^{+}INF^{+}{}_{i,t} + u_{i,t}.\,\mathbf{3.4.6}\,*$$

Where HCSD denoted the harmonised (consistent) indicator (s) of human capital skills across the sub-regional economic blocs in SSA, meanwhile INF captures the harmonised (consistent) indicator (s) of infrastructure across the sub-regional economies in SSA. The control indicators donated GCF and FDI across the sub-regions in SSA. The harmonised model 3.46* exemplified the simple explicit form of the previous models from 3.4.7 to 3.4.16 in one fold to curb complexity in the cause of the econometric analysis. Also, the harmonised model 3.46* was expanded from 3.46** to 3.46***** for sub-regional specifics.

Consequently, it is important to properly identify the specific value of each estimate for econometric analysis by disclosing their order of true identity as coefficient elasticity β_0, β_1, β_2………… βn.

$$logGCF^{+}{}_{i,t} = \sum_{j=1}^{p} \triangle\, logGCF^{+}{}_{i,t} = \sum_{j=1}^{p} max\big(\triangle\, logGCF_{i,t}, 0\big),$$

$$logGCF^{-}{}_{i,t} = \sum_{j=1}^{p} \triangle\, logGCF^{-}{}_{i,t} = \sum_{j=1}^{p} min(\triangle\, logGCF_{i,t}, 0) \ldots \ldots \ldots 3.4.6 **$$

Where $\triangle\, logGCF^{+}{}_{i,t}$ and $\triangle\, logGCF^{-}{}_{i,t}$ denote the increase and decrease in GCF effects across the sub-regional economies. p is the optimal lag.

$$logFDI^{+}{}_{i,t} = \sum_{j=1}^{p} \triangle\, logFDI^{+}{}_{i,t} = \sum_{j=1}^{p} max\big(\triangle\, logFDI_{i,t}, 0\big),$$

$$logFDI^{-}{}_{i,t} = \sum_{j=1}^{p} \triangle\, logFDI^{-}{}_{i,t} = \sum_{j=1}^{p} min(\triangle\, logFDI_{i,t}, 0) \ldots \ldots \ldots 3.4.6 ***$$

Where $\triangle\, logFDI^{+}{}_{i,t}$ and $\triangle\, logFDI^{-}{}_{i,t}$ denote the increase and decrease in FDI effects across the sub-regional economic blocs in SSA.

$$logHCSD^{+}{}_{i,t} = \sum_{j=1}^{p} \triangle\, logHCSD^{+}{}_{i,t} = \sum_{j=1}^{p} max\big(\triangle\, logHCSD_{i,t}, 0\big),$$

$$logHCSD^{-}{}_{i,t} = \sum_{j=1}^{p} \triangle\, logHCSD^{-}{}_{i,t} = \sum_{j=1}^{p} min(\triangle\, logHCSD_{i,t}, 0) \ldots \ldots \ldots 3.4.6 ****$$

Where $\triangle\, logHCSD^{+}{}_{i,t}$ and $\triangle\, logHCSD$ denote the increase and decrease in HCSD effects across the sub-regional blocs in SSA.

$$logINF^{+}{}_{i,t} = \sum_{j=1}^{p} \triangle\, logINF^{+}{}_{i,t} = \sum_{j=1}^{p} max\big(\triangle\, logINF_{i,t}, 0\big),$$

$$logINF^{-}{}_{i,t} = \sum_{j=1}^{p} \triangle\, logINF^{-}{}_{i,t} = \sum_{j=1}^{p} min(\triangle\, logINF_{i,t}, 0) \ldots \ldots \ldots 3.4.6 *****$$

Where $\triangle\, logINF^{+}{}_{i,t}$ and $\triangle\, logINF^{-}{}_{i,t}$ denote the increase and decrease in FDI effects across the sub-regional blocs in SSA.

3.3.4.1.2 Reviewing Panel Cointegration for Long-Run Hypothesis

Also, other necessary conditions must be fulfilled to disclose the long-rung asymmetric effects of human capital skills and infrastructure on industrial output growth across SSA economic blocs. Necessary conditions such as lag length criteria, Bounds Cointegration testing, and Padroni's panel cointegration test must be reviewed. Therefore, NARDL models in 3.4.7--3.4.16 and 3.4.6*--3.4.6***** are modified for the long-run asymmetric effects in models 3.5i and 3.5ii across individual sub-regions in SSA, which is consistent with (Padroni, 2004), (Shin et al., 2014) and Sama et al., (2023) thus;

$$\begin{aligned}\triangle logIDO_i = \beta_0 &+ \sum_{j=1}^{p} \beta_1 \triangle logIDO_{i-1} + \sum_{j=0}^{p} (\beta_2{}^{+} logGCF^{+}{}_{i-1} + \beta_3{}^{-} logGCF^{-}{}_{i-1}) \\ &+ \sum_{j=0}^{p} (\beta_4{}^{+} logFDI^{+}{}_{i-1} + \beta_5{}^{-} logFDI^{-}{}_{i-1}) + \sum_{j=0}^{p} (\beta_6{}^{+} logSER^{+}{}_{i-1} \\ &+ \beta_7{}^{-} logSER^{-}{}_{i-1}) + \sum_{j=0}^{p} (\beta_4{}^{+} logLPR^{+}{}_{i-1} + \beta_5{}^{-} logLPR^{-}{}_{i-1}) \\ &+ \sum_{j=0}^{p} (\beta_6{}^{+} logLBF^{+}{}_{i-1} + \beta_7{}^{-} logLBF^{-}{}_{i-1}) + \sum_{j=0}^{p} (\beta_4{}^{+} logACE^{+}{}_{i-1} \\ &+ \beta_5{}^{-} logACE^{-}{}_{i-1}) + \sum_{j=0}^{p} (\beta_6{}^{+} logACT^{+}{}_{i-1} + \beta_7{}^{-} logACT^{-}{}_{i-1}) \\ &+ \sum_{j=0}^{p} (\beta_4{}^{+} logICT^{+}{}_{i-1} + \beta_5{}^{-} logICT^{-}{}_{i-1}) + \sum_{j=0}^{p} (\beta_6{}^{+} logAWP^{+}{}_{i-1} \\ &+ \beta_7{}^{-} logAWP^{-}{}_{i-1})\end{aligned}$$

…………………….3.5i

Harmonized panel models for sub-regional cointegration specifics thus;

$$\begin{aligned}\triangle logIDO_i = \beta_0 &+ \sum_{j=1}^{p} \beta_1 \triangle logIDO_{i-1} + \sum_{j=0}^{p} (\beta_2{}^{+} logGCF^{+}{}_{i-1} + \beta_3{}^{-} logGCF^{-}{}_{i-1}) \\ &+ \sum_{j=0}^{p} (\beta_4{}^{+} logFDI^{+}{}_{i-1} + \beta_5{}^{-} logFDI^{-}{}_{i-1}) + \sum_{j=0}^{p} (\beta_6{}^{+} logHCSD^{+}{}_{i-1} \\ &+ \beta_7{}^{-} logHCSD^{-}{}_{i-1}) + \sum_{j=0}^{p} (\beta_4{}^{+} logINF^{+}{}_{i-1} + \beta_5{}^{-} logINF^{-}{}_{i-1})\end{aligned}$$

………………..….3.5ii

Where $\sum_{j=1}^{p} \beta_1^{+}$ & $\sum_{j=1}^{p} \beta_1^{-}$ explained the short-run positive and negative asymmetric effects. To ascertain the long-run asymmetric effects, a cointegration test is considered under this condition, and specific hypotheses are drawn as follows:

H_0: ($\gamma^{-} = \gamma^{+} = 0$; $\forall_I = 1, 2, 3$……., 5) There is presence of a long-run effect and cointegration.

H_0: ($\gamma^{+} \neq \gamma^{-} = 0$; $\forall_I = 1, 2, 3$……., 5) There is absence of a long-run effect and cointegration.

Where γ^{-}& γ^{+} explained the generally negative and positive long-run asymmetric effects of GCF, FDI, and HCSD's harmonised (consistent) indicator (s) (i.e. SER, LPR, LBF, LIR) and INF's the harmonised (consistent) indicator (s) (i.e. ACE, ACT, ICT, AWP) on IDO, also, γ^{-}& γ^{+} explained the harmonized panel negative and positive long-run asymmetric effects of HCSD and INF. Recall u_(i,t) in the partial sum model in 3.19 explained the stochastic error terms while p explained the length of the maximum lag being considered in the model, which was guided by different criteria such as AIC, among others. △ Implied first difference operator while t explained the period.

The next step is to compare the F-statistic with the two criteria bounds suggested by Pedroni (2004) and Pesaran et al. (2003) to ascertain the extent of connections among the estimates as the lower critical bound clarified the first-order critical figures, which shoulders that the estimates are integrated at zero order I(0) while the upper critical bound is another set of critical figures, which undertakes the estimates that are integrated at order one I(1). Hence, when the F-statistic is greater than the upper critical bound and vice versa, the H_0 is rejected while the H_I of the presence of cointegration cannot be rejected. However, when the F-statistic lies between the limits, it is undecided.

3.3.5 Examining Pedroni's Cointegration Test

Based on the study's objectives, a panel cointegrating test would be more logical to test for long-run cointegration among the dataset. Unlike the conventional time-series analysis using Bounds testing, this Padroni assertion relies on normalization or the number of cointegrating interactions. Instead, the hypothesis test is concise and direct to ascertain the degree of cointegrating evidence in a panel model, particularly among two or more variables (Neal, 2014). Padroni grouped seven test statistics into two sets: the average, the discrete country statistic test results, and the panel statistics test to pool all the statistics within the within-dimension through group-average statistics.

The parametric (augmented Dickey-Fuller [ADF] and less-parametric (i.e. ρ and t) tests statistic falls within the two groups. Typical time dummies via residuals to address simple cross-sectional dependency, using time demeaning of the dataset, are mainly applied thus.

$$y^{-} = \frac{1}{N}\sum_{i=1}^{N} Y_{\mathrm{i}}, t$$

Note: ***Pedroni's*** test statistics were residual-centered tests through the panel regression in model 3.4.6* linked to become model 3.6 and explored through panel unit root model in 3.6i thus;

$$logIDO_{i,t} = \beta_0 + \beta_1^{-} logGCF^{-}{}_{i,t} + \beta_2^{+}\mathrm{log}FDI^{+}{}_{i,t} + \beta_3^{-}HCSD^{-}{}_{i,t} + \beta_4^{+}INF^{+}{}_{i,t} + u_{i,t} \ in \ \mathbf{3.4.6} *$$

$$\triangle \, logIDO_i = \beta_0 + \sum_{\beta=1}^{\beta} \beta_1 \triangle \, logGCF_{i-1} + \sum_{\beta=1}^{\beta} \beta_2 \triangle \, logFDI_{i-1} + \sum_{\beta=1}^{\beta} \beta_1 \triangle \, logHCSD_{i-1} + \sum_{\beta=1}^{\beta} \beta_1 \triangle \, logINF_{i-1}$$

…………………3.6

$e_{i,t} = \_idoi\_ei,_{t-1} + \_\mu_{i,t} \_e_{i,t} = \_idoi\_e_{i,t-1} + \_K_{k=1} \_ido_{i,k} \Delta\_e_{i,t-k} + \_\mu * _{i,t}\_e_{i,t} = \_idoi\_e_{i,t-1} + \_\mu_{i,t}$

…………………3.6i

Where i = 1, 2. . . N is the number of entities in the panel, t = 1, 2. . . T is the number of periods, m = 1, 2. . . *GCF, FDI, HCSD and INF* are the regressors, and k = 1, 2. . . K is the number of lags in the ADF regression (automatically by E-views or by xtpedroni along other options). Also, time trend δit can be introduced into the regression based on the user's discretion. Hence, some analyses were calculated from the regressions above.

Notably, now that the models for the long-run asymmetric effects are established, the next step is to conduct an error correction model (ECM) to ascertain the speed of adjustment between the short-run and long-run models. The ECM can be stated in models 3.7 and 3.7i as follows:

$$\triangle logIDO_i = \beta_0 + \sum_{j=1}^{p} \beta_1 \triangle logIDO_{i-1} + \sum_{j=0}^{p} (\beta_2{}^{+} logGCF^{+}{}_{i-1} + \beta_3{}^{-} logGCF^{-}{}_{i-1})$$
$$+ \sum_{j=0}^{p} (\beta_4{}^{+} logFDI^{+}{}_{i-1} + \beta_5{}^{-} logFDI^{-}{}_{i-1}) + \sum_{j=0}^{p} (\beta_6{}^{+} logSER^{+}{}_{i-1}$$
$$+ \beta_7{}^{-} logSER^{-}{}_{i-1}) + \sum_{j=0}^{p} (\beta_4{}^{+} logLPR^{+}{}_{i-1} + \beta_5{}^{-} logLPR^{-}{}_{i-1})$$
$$+ \sum_{j=0}^{p} (\beta_6{}^{+} logLBF^{+}{}_{i-1} + \beta_7{}^{-} logLBF^{-}{}_{i-1}) + \sum_{j=0}^{p} (\beta_4{}^{+} logACE^{+}{}_{i-1}$$
$$+ \beta_5{}^{-} logACE^{-}{}_{i-1}) + \sum_{j=0}^{p} (\beta_6{}^{+} logACT^{+}{}_{i-1} + \beta_7{}^{-} logACT^{-}{}_{i-1})$$
$$+ \sum_{j=0}^{p} (\beta_4{}^{+} logICT^{+}{}_{i-1} + \beta_5{}^{-} logICT^{-}{}_{i-1}) + \sum_{j=0}^{p} (\beta_6{}^{+} logAWP^{+}{}_{i-1}$$
$$+ \beta_7{}^{-} logAWP^{-}{}_{i-1}) + \theta ECT_i + U_i$$

…………3.7

Harmonized panel models for sub-regional ECM cointegration specifics thus;

$$\triangle logIDO_i = \beta_0 + \sum_{j=1}^{p} \beta_1 \triangle logIDO_{i-1} + \sum_{j=0}^{p} (\beta_2{}^{+} logGCF^{+}{}_{i-1} + \beta_3{}^{-} logGCF^{-}{}_{i-1})$$
$$+ \sum_{j=0}^{p} (\beta_4{}^{+} logFDI^{+}{}_{i-1} + \beta_5{}^{-} logFDI^{-}{}_{i-1}) + \sum_{j=0}^{p} (\beta_6{}^{+} logHCSD^{+}{}_{i-1}$$
$$+ \beta_7{}^{-} logHCSD^{-}{}_{i-1}) + \sum_{j=0}^{p} (\beta_4{}^{+} logINF^{+}{}_{i-1} + \beta_5{}^{-} logINF^{-}{}_{i-1}) + \theta ECT_{\mathrm{i}} + U_{\mathrm{i}}$$

……….3.7i

θ captures the coefficient of the error correction term-ECT that explains the speed of adjustment from the point equilibrium in the short run under a specific lag length criterion estimated in the NARDL model to the point of equilibrium in the long run. The rule of thumb is that it is expected that the value of ECT must be negative and fall between 0 and 1 in absolute value. The next step is conducting a series of diagnostics tests, such as Wald and CUSUM and CUSUM-Square tests, to ascertain the results' reliability and validity.

3.4 JUSTIFICATIONS FOR THE EMPIRICAL VARIABLES OF MEASUREMENTS

The broad and all-inclusive estimates are used to explain all the variables employed in the study, which are specified as follows:

$$IDO = f\ (LPR, LBF, SER, LFE, LIR, GCF, AYS, ICT, AWP, LER, HOC, FDI) \ldots (3.8)$$

Concepts of the Study	Variable(s) of Measurements	Explanation of the Variable(s)	Justifications for the Variable(s)
Measurements of Industrial Sector Growth	**Industrial Output Growth (IDO)**	Annual Industrial Output from individual SSA countries. That is Yearly value-added industrial output data.	It allows the study to capture the rate at which industrial production subsists across the SSA region regarding value addition and content produced.
Measurements of Human Capital	**Labour Participation Rate (LPR)**	The proportion of the nation's skilled labour force that was energetically supplied and engaged in the labour market, either employed or not engaged with a job.	This variable is used to estimate labour skills applied to industrial productivity. It specifically measures the level of advanced skills that affect industrial growth. Innovative and Intellectual skills of labour are given attention here.
	Labour Force (LBF)	Total number of the nation's skilled working and non-working populace in the aggregate economy, either engaged or not with a job at a particular time.	Including this variable is to capture both gross skilled and gross unskilled labour that actively engages in productivity. This variable measures units of input by the labour based on the level of skills they possessed
	School Enrollment rate (SER) is *a major*	Entire entrance in a certain level of education (primary,	This variable estimates sources

	source of skills acquisition.	secondary and tertiary), irrespective of age, is stated as a proportion of the certified school-age populace for the equal education rate**.**	of labour's knowledge/skills acquisition. This variable measures the extent of knowledge attained by labour over time, primarily through former studies.
	Household Consumption (HOC)	This variable encompasses several determinants of human capital skill development, such as access to a conducive environment, good roads, clean energy, and water, among others, while undergoing training or skill acquisition.	This is to estimate the extent of labour working conditions either during informal or formal training or when he/she is actively engaged in productivity. This variable is a valid instrument in the study.
	Average Years of Schooling (AYS)	Mean index period spent by people on education, ages 25 and older, with a transformation from education completion points to certification on official durations for each level. Notably, this variable is incorporated to ascertain possible gains and losses of time lost for knowledge acquisition.	This is to address opportunity cost, i.e. time forgone for training. It estimates the average time spent by labour in acquiring training from entry-level to graduation and how this knowledge has improved output growth.
	Literacy Rate (LIR) **Other control measures like LER, TRT, HCI, and SYE are in the appendixes.**	A fraction of the populace aged 15 and older can read and write a short and straightforward report on everyday activity.	This variable would provide us with the skills labour applied during production due to the knowledge that labour attained through formal or informal training or education.

Measurements of Infrastructural Development	**Industrial Growth Dynamics: Via Technology such as the application of Information Communication Technology (ICT)**, **Technology Produced/ Export(TEP), etc.**	This contains how the introduction of technology aids the transfusion and diffusion of knowledge from traditional production to modern productivity.	The data leverages primitive skills and up-to-date skills. It is used to estimate the transformation period that catalyses SSA's industrial growth.
	Access to Energy/Electricity (ACE): *As the indispensable infrastructure measure.* **Access to Foreign Direct Investment (FDI)** **Access to Transportation (ACT),** **Access to Water Resources (AWP)**	**ACE:** This contains how industries can access power supply for output growth. **FDI:** Foreign Direct Investment, especially via Infrastructure, as the control variable. **ACT:** This contains how industries can access transport networks for output growth. **AWP:** This contains how industries can access purified water resources for output growth.	The data explains infrastructure spread through energy, transport, and water supply across households and industrial estates. Of course, it has a general impact on output growth in SSA.
	Gross Capital Formation (GCF) **Other measures and instruments like ACR, PPE, PPT, and PPW were explained in the appendixes.**	Expenses on gains to the economy's fixed assets and net stock differences. Fixed assets are land (site) developments, siting of the industrial estate, building plants, equipment, etc.	This variable estimates the basic level of the country's investment in technology across SSA economies. This is to measure the technical level of technology in an economy.

Source: Author's Computation, (2022)

3.5 APRIORI EXPECTATIONS

This area is pertinent to models specified in the study, most importantly models 3.19 and 3.3.1, which explained the link between industrial output growth (Y_{it}), human capital (hL_{it}) and infrastructure (K_{it}) on industrial growth via indicators of human capital (hL_{it}) and infrastructure

(K_{it}). Moreover, models 3.2.1, 3.3.19 and 3.5 are also important. For example, these models reveal the sources of human capital, infrastructure, and industrial output growth from the empirical and theoretical points of view as follows: $\frac{\partial logh_{i,t}}{\partial logA_{i,t}} > 0, \frac{\partial logh_{i,t}}{\partial logK_{i,t}} > 0, \frac{\partial logh_{i,t}}{\partial logY_{i,t}} > 0, \frac{\partial logh_{i,t}}{\partial logL_{i,t}} >< 0$ and $\frac{\partial logK_{i,t}}{\partial logA_{i,t}} > 0, \frac{\partial logK_{i,t}}{\partial logL_{i,t}} > 0, \frac{\partial logK_{i,t}}{\partial logY_{i,t}} > 0, \frac{\partial logK_{i,t}}{\partial logh_{i,t}} >< 0,$ which means that except for $\frac{\partial logh_{i,t}}{\partial logL_{i,t}} >< 0, \frac{\partial logK_{i,t}}{\partial logh_{i,t}} >< 0,$ in models 3.2.19 and 3.3.1 that disclose diverse relationships, depending on how the variables respond to one another.

3.6 EMPIRICAL TECHNIQUES

The empirical methods adopted in this study varied regarding the study's set objectives. Also, these techniques were employed to determine the specified models based on set objectives.

3.6.1 Panel Data Analysis

Objectives one, two and three in this study were carried out with panel data analysis. This means the factors determining industrial sector growth were investigated via these methods. Also, the comparative effects of human capital skill development and the infrastructural improvement across the sub-regional economic blocs were estimated using the sub-sampling regression, FE-LSDV, and two-step system GMM panel data approach. Furthermore, the third objective was carried out through panel threshold regression and NARDL model analysis. The panel data analysis begins with a panel summary of statistics, as it is pertinent to all the estimates employed and specified in the panel model to be normally and statistically distributed. First and second-generation Unit root tests were conducted, and cross-sectional dependence tests were carried out to establish stationarity in the panel data and the likelihood of cross-section dependence among the series.

Notably, **f**our options are open for panel data analysis. Each of these options is reviewed thereof. Notably, the N and T series employed in the study are N=40, T-32; that is, the N>T number of cross-sections must be greater than the time lag (span) (Arellano, 1986; Seo et al., 2016; Adeleye, 2018; Akinola & Mbonigaba, 2019).

3.6.2 Panel Unit Root Tests: Cross-Sectional Dependence and Structural Break(S)

One of the essential features of time-series data is stationarity. A stationary time series forms the bedrock for accurate statistical analysis—the stationarity of data signals that all standard measurement tools can apply. The series can be regressed in models via the appropriate econometric intuition, a useful instrument for the estimated mean and variance and empirical discoveries. Frequently, there are different conditions for time series stationarity, nonstationary, or unit-root as predicated by their statistical modelling. For example, if nonstationarity is not accounted for, this may lead to biased inferences and predictions arising from inference and prediction, which might bring about spurious regression outcomes (Chen, Karavias & Tzavalis, 2022). A spurious regression brings superfluous R-Square and biased statistically significant coefficients when there might be no relationship among the estimated series. Therefore, it is pertinent in this study to determine whether a series is stationary in any time series and panel data (that contain various cross sections of time series) analysis.

Hurlin and Mignony (2006) argued that the investigation of integrated order of series in panel data has been a breakthrough in panel unit root tests, which apply to different aspects of economic specialization such as growth and convergence issues, savings, investment dynamics, comparative analysis, and non-linear estimations, among others. Panel unit-root tests are employed in the study to statistically conduct hypothesis tests to establish whether a series has a unit root or a stationary one. To ascertain the presence of cross-section dependence and assess whether structural breaks in data affect the panel unit root test coefficients.

3.6.2.1 A First Generation Unit Root Test

The traditional unit root test is becoming outdated due to gains from the first generation panel unit root tests. In the works of Levin, Lin, and Chu (2002), it was empirically proved that there was an improvement in unit root tests through panel data compared to the conventional univariate approach. This improved panel unit root test showed characteristics of the data in the panel model before testing for the empirical relationships. This idea revolves around the stationarity test of individual variables employed in the study. The Levin, Lin and Chu (LLC) test is applied in balance data and is pertinent in testing whether the error term is independently spread across the panels and follows a stationary Autoregressive Moving Average (ARMA) for each panel. Notably, LLC suggests using their test with a penal of "moderate" size, which comprises between 1 to 250 panels and 25 to 250 observations per panel. Consequently, the LLC panel unit root test aligns with the balance panel data analysis, which is relevant to this study.

Also, Engel and Granger (1997) posit that, at first instance, a series may not be stationary, whereas a linear mixture of the non-stationary series may be stationary. Therefore, a unit root test is necessary to uncover any form of hidden co-integration. Another relevant panel of unit root tests followed in the study is the Im, Pesaran and Shin (IPS) test. This test is relevant for investigating panel stationarity of series (Im, Pesaran & Shin, 2003; Hlouskova & Wagner, 2005; Ramalingam & Gangai, 2020). The simple IPS description is expressed as:

$$\Delta Y_{i,t} = aY_{i,t-1} + \sum_{j=1Yij}^{Pi} \Delta Y_{i,t-j} + \beta_0 + \beta_{1t} + \beta_1 x_{i,t} + \mathcal{E}_{i,t} \dots\dots\dots\dots\dots\dots\dots (3.9)$$

Where βo is the constant, X $_{i,t}$ denotes the independent series, $\Delta Y_{i,t}$ account for the dependent series, β_{1t} captures time and trend, while P explains the lag length required. The null hypothesis for the IPS denotes as H_0: $\alpha_1 = 0$ for all "i"s while the alternate hypothesis, H_1: $\alpha_i < 0$, is tested for at least one i. Interestingly, instead of pooling the data, IPS disaggregated the unit root tests for the N cross-section units, which directed the tests towards the Augmented Dickey-Fuller statistics at an averaged level across the panels. Based on this pertinent assumption of cross-sectional independence, normal distribution is achieved as the statistics sequentially converge, especially when T is high along with N.

Furthermore, Im, Pesaran, and Shin's (1997, 2003) arguments for the panel unit root test are further expanded to address this study's assumption of cross-sectional independence. Meanwhile, the LL test allows for heterogeneity in the i value under the alternative hypothesis. IPS considered the model (1) and substituted i for their model with individual effects, and no time trend is now:

$$\Delta y_{i,t} = \alpha_i + \rho_i y_{i,t-1} + \sum_{z=1}^{p_i} \beta_{i,z} \Delta y_{i,t-z} + \varepsilon_{i,t} \dots\dots\dots\dots\dots (3.10)$$

The third null hypothesis is presented as H0 : i = 0 for all i = 1;:::;N and the alternative hypothesis is H1 : i < 0 for i = 1;:::;N1 and i = 0 for i = N1 + 1;:::;N; with 0 < N1 N.

The alternative hypothesis encompasses more (but not all) of the specific series to possess unit roots. Therefore, instead of pooling the data, IPS uses separate unit root tests to determine the number of cross-sections. This test rested on the Augmented Dickey-Fuller statistics mean across groups.

Supposed ti T (pi; i) with i = i;1;:::; i; pi signify the t-statistic for testing unit root in the ith country, the IPS statistic is then signalled as:

$$t\_bar_{NT} = \frac{1}{N}\sum_{i=1}^{N} t_{iT}\left(p_i, \beta_i\right) \quad \ldots\ldots\ldots\ldots\ldots\ldots \text{(3.11)}$$

As it was explained earlier, based on the key assumption of cross-sectional independence, IPS statistics disclosed sequentially converge to a normal distribution when T inclines to infinity, trailed by N. Intuitively, when T tends to infinity, each statistic ti T (pi; i) converges to the Dickey-Fuller distribution.

Also, different tests make different assumptions about the conditions of the number of panels, N, and the periods, T, tend to infinity or whether N or T is fixed. For example, in a microeconomic panel of firms in an industry, rising N would involve gathering additional data of more firms while holding the number of times T fixed; here, N tends to infinity, whereas T is fixed. From another perspective, in macroeconomic analysis of SSA countries, one would typically assume that N is fixed, whereas T tends to increase. Hence, it is pertinent in the study to show the cross-sectional dependence and possible shocks from structural breaks. Akaike Information Criterion option is adopted to select the lag length criteria.

3.6.2.2 A Second Generation Unit Root Test

The second generation panel unit root tests lessen the burden of the cross-sectional independence assumption. This is to downplay the specification of cross-section dependence because it does not possess the natural ordering. So, in addressing this, two groups can be separated as cross sections for dynamic factor model and non-restrictive covariance matrix residuals.

Pesaran (2003) proposes a different method to address cross-sectional dependency problems via a one-factor model with heterogeneous loading factors for residuals. However, he augmented the standard Dickey-Fuller with the cross-section mean of the lagged levels and residual differences of the individual series instead of using the unit root tests on deviations from the assessed common factors. Supposed the residuals are not serially correlated, the regression adopted for the ith country is presented as:

$$yi;t\ = i\ +\ iyi;t\ 1\ +\ ciyt\ 1\ +\ diyt\ +\ vi;t\text{……….. (3.12)}$$

Where $\bar{y}_{t-1} = (1/N)\sum_{i=1}^{N} y_{i,t-1}$ and$\Delta y_t = (1/N)\sum_{i=1}^{N} \Delta y_{i,t}$: Let ti (N; T) as the t-statistic of the OLS estimate of i. The Pesaran's test rested on these individual crosssectionally augmented ADF statistics, signalled as CADF.

3.6.2.3 Panel Unit-Root Tests with Structural Breaks

In a related scenario, structural break(s) are pertinent in panel unit root data analysis. Breaks might predict the behaviour of unit-root tests. Structural breaks are such as shocks, which are exogenous to the model but influence it via parameter estimates. Breaks happen when rapid change springs up, such as economic phenomena such as pandemics like COVID-19 wars, policy reconfiguration, and financial meltdowns. These shocks might make stationary series non-stationary, while in some cases, they might not have significant effects on the estimated series. Hence, Perron (1989) came up with new unit root tests that allow for a structural break in the constant and trend of the series. Perron’s approach, however, assumed that the date of the structural break is known to the researcher. In further answer, Karavias and Tzavalis (2014) proposed panel-data unit-root tests that allow for structural breaks in the intercepts of the series or in both the intercepts and linear trends. The break dates are assumed to be typical for all series, but the magnitude of the break can differ across series.

Karavias and Tzavalis (2014) argued for two models in the case of panels with N cross-section components and T time-series data with one common break. The first model accounts for the null hypothesis of a random walk against the alternative hypothesis of a stationary series with a break in the intercepts (means) of the series,

$$Ho{:}\, yi,t\ =\ yi,t-1\ +\ ui,t \dots\dots\dots\dots \text{ (3.13)}$$

$$Hi{:}\, yi,t\ =\ \phi yi,t-1\ +\ (1\ -\ \phi)\{a1,iI(t\ \le\ b)\ +\ a2,iI(t\ >\ b)\}\ +\ ui,t \dots\dots.\text{(3.14)}$$

Where $i = 1 \dots N$ and $t = 1,\dots,T$. In the above model, ϕ is the autoregressive parameter, and $a1,{}_i$ and $a2;{}_i$ are the fixed effects before and after the break, which happens on date b. The notation $I(\cdot)$ shows the indicator function. The second model tests the null hypothesis of a random walk with drift against the alternative of a trend-stationary panel process with a break in the intercepts and linear trends at time b:

$$Ho: yi,t = yi,t-1 + \beta i + ui,t$$

and

$$Hi: yi,t = \phi yi,t-1 + \phi\{\beta 1,iI(t \le b) + \beta 2,iI(t > b)\} + (1-\phi)\{a1,iI(t \le b) + a2,iI(t > b)\} + (1-\phi)\{\beta 1,itI(t \le b) + \beta 2,itI(t > b)\} + ui,t \dots\dots\dots (3.15).$$

In the above formulation, β_i is the point under the null hypothesis, while $\beta_{1,\,i}$ and $\beta_{2,\,i}$ are the trend coefficients under the alternative hypothesis. Henceforth, we will classify 3.18iv as the model with intercepts (1) and 3.18v as the model with intercepts and trends (2). Importantly, under 3.18iv, the break is allowed to be in $I_1 = \{1,2,\dots,T-1\}$, and 3.18v break is allowed to be in $I_2 = \{2,\dots,T-2\}$. The alternative hypothesis is homogeneous across different individuals, but Karavias and Tzavalis (2016) have shown that the test has power against heterogeneous alternatives as well, when ϕ_i =6 ϕ_j and $\phi_i,\phi_j < 1$ for $i,j = 1,\dots, N$ and i 6= j. Juodis, Karavias, and Sarafidis (2021) also compared the gains of power pooled estimators to those of power mean-group-type estimators like Im, Pesaran, and Shin (2003).

Summary of different key Procedures among Panel Unit Root Testing

Test	Options	Asymptotics	ρ under H_a	Panels
LLC	no constant		common	balanced
LLC		$\sqrt{N}/T \to 0$ $N/T \to$ $N/T \to$ 0	common	balanced
LLC	trend	0	common	balanced
HT	no constant	$N \to \infty$, T fixed	common	balanced
HT		$N \to \infty$, T fixed	common	balanced
HT	trend	$N \to \infty$, T fixed	common	balanced
Breitung	no constant	$(T, N) \to_{seq} \infty$	common	balanced
Breitung		$(T,N) \to_{seq} \infty$	common	balanced

Breitung	trend	$(T,N) \rightarrow_{seq} \infty$	common	balanced
IPS		$N \rightarrow \infty$, T fixed, or N and T fixed	panel-specific	unbalanced
IPS	trend	$N \rightarrow \infty$, T fixed, or N and T fixed	panel-specific	unbalanced
IPS	lags()	$(T, N) \rightarrow_{seq} \infty$	panel-specific	unbalanced
IPS	trend lags()	$(T, N) \rightarrow_{seq} \infty$	panel-specific	unbalanced
Fisher-type		$T \rightarrow \infty$, N finite or infinite	panel-specific	unbalanced
Hadri LM		$(T, N) \rightarrow_{seq} \infty$	(not applicable)	balanced
Hadri LM	trend	$(T, N) \rightarrow_{seq} \infty$	(not applicable)	balanced

The first column ascertains the test procedure. LLC signifies the Levin–Lin–Chu test, HT represents the Harris–Tsavalis test, and IPS means the Im–Pesaran–Shin test. Meanwhile, the second column indicates the deterministic components included in (1) or (10). The column labelled "Asymptotics" means the N's behaviour in the panels, and periods, T, required for the test statistic to have a well-defined asymptotic distribution. For example, if the LLC test is carried out without the non-constant option, it means that T grow at a faster rate than N so that N/T approaches zero; with the non-constant option, we need only for T to grow faster than the square root of N (so T could grow more slowly than N).

The HT tests and the IPS tests without accommodations for serial correlation, where it is assumed that the number of periods, T, is fixed, while N tends to infinity; xtunitroot also reports critical values for the IPS tests that are valid in finite samples (where N and T are fixed). Many tests are justified using sequential limit theory, which we signify as $(T, N) \rightarrow_{seq} \infty$. First, the time dimension goes to infinity, and then the number of panels goes to infinity. As a practical matter, these tests work best with "large" T and at least "moderate" N. Phillips and Moon (2000) emphasised the asymptotics that depend on N and T and their connection to nonstationary panels. Phillips and Moon (1999) discussed "multi-indexed" asymptotics more technically.

The fourth column refers to the parameters ρi in (1) and φi in (10). As stated earlier, some tests assumed that all panels have a similar autoregressive parameter under the alternative hypothesis of stationarity (signified as "common" in the table). In contrast, others allow for panel-specific autoregressive parameters (represented as “panel-specific” in the table). The Hadri LM tests are not framed regarding an equation like (1) or (10), so the distinction based on ρ is not applicable. The final column disclosed whether the panel dataset must be strongly balanced. That is, each of the panels has the same number of observations covering the same period. Except for the Fisher tests, all the tests require no gaps in any panel’s series.

Notably, this study took account of the two directions of panel unit root research that have been developed since the Levin and Lin (1992) seminar work, which paved the way for the two generations of panel unit root tests. Precisely, the first generation duels on heterogeneous modellings and cross dependence with the contributions of Im, Pesaran and Shin (1997; 2003), Maddala and Wu (1999), Choi (2001) and Hadri (2000). The second duels much on more recent research, which addressed the cross-sectional dependencies and structural breaks (Karavias & Tzavalis, 2014; 2016).

3.6.3 Panel Correlation Analysis

This is part of the pre-estimation test to ascertain the level of relationship between the explanatory variables and the explained variable. It was empirically established in the study to address possible multicollinear problems that may arise through panel data rather than the conventional univariate approach. This improved panel correlation test shows the data's characteristics and relationships in the panel model before testing for the panel data analysis. This idea revolves around the attributes of individual variables employed in the study.

3.6.4 The Fixed Effect Model

This model explains how the shift parameter is time-variant. The assumption is that the intercept is a time-variant across the cross-sectional series.

1 **Within-Group Fixed Effects:** In this form, the mean average of the series in the model on a given data is measured and deducted from the estimated individual information thus;

$$\mathrm{Y}_{\mathrm{it}} - \hat{\mathrm{Y}}_{\mathrm{i}} = \sum_{i=2}^{k} \beta_i (X_{ijt} - \overline{X}_{ij}) + \partial(\mathrm{t} - \bar{\mathrm{t}}) + \mathrm{E}_{\mathrm{it}} - \bar{\mathrm{E}}_{\mathrm{i}} \qquad \text{---------------} (3.16)$$

Consequently, the undetected impact fades away, which refers to the regression model within groups.

2 **First Difference Fixed Effect:** Under this option, the unobserved effect fades away after removing the observation of the past period from the current period in all periods. Hence, the model is specified for individual data i over time t. For the current period, the link is specified as;

$$\mathrm{Y}_{\mathrm{it}} = \beta_i + \sum_{j=2}^{k} \beta_j X_{ijt} + \partial \mathrm{t} + \sigma_i + \mathrm{E}_{\mathrm{it}} \qquad -----------(3.17)$$

While for the past year or period, the link is expressed as

$$\mathrm{Y}_{\mathrm{it\,\text{-}1}} = \beta_i + \sum_{j=2}^{k} \beta_j X_{ijt} - 1 + \partial(\mathrm{t}\,\text{-}1) + \sigma_i + \mathrm{E}_{\mathrm{it\,\text{-}1}} \qquad ---------------(3.18)$$

Deducting (3.19) from (3.20), it becomes;

$$\Delta \mathrm{Y}_{\mathrm{it}} = \sum_{j=2}^{k} \beta_j \Delta X_{ijt} + \partial + \mathrm{E}_{\mathrm{it}} - \mathrm{E}_{\mathrm{it\,\text{-}1}} \qquad -------(3.19)\,.$$

Consequently, the unnoticed heterogeneity vanishes away.

3.6.5 Least Square Dummy Variable Fixed Effect (LSDV)

In this case of a panel regression model, it is assumed to capture differences across the determinants variable through differences in their constant level. It helps us to see the unobserved effect in the model. Assuming we express a set of dummy series d_i, where d_i is set to be *1* in the case of an observation relating to data *i* and *0* otherwise, which can be expressed as;

$$\mathrm{Y}_{\mathrm{it}} = \sum_{j=2}^{k} \beta_j X_{ijt} + \partial \mathrm{t} + \sum_{t=1}^{n} \sigma_i d_i + \mathrm{E}_{\mathrm{it}} \qquad ----------------(3.20)$$

Consequently, the unobserved effect is injected, referred to as the individual co-efficient of the specified dummy variable.

3.6.6 Random Effect Model

The last option, open to panel model regression, is explained. Interestingly, this option is subject to two conditions in which they answer the problems associated with the fixed effects model, mainly when the key variable is time-invariant for each entity, and such a variable cannot be employed. The first condition assumes the likely use of the first undetected Z_p series as it is drawn randomly from a data set. Furthermore, this could be the case subject to the individual observations comprising a random sample from a set population. Assuming;

$$\mathrm{Y}_{\mathrm{it}} = \beta_j + \sum_{j=2}^{k} \beta_j X_{ijt} + \partial_{\mathrm{t}} + \sigma_i + \mathrm{E}_{\mathrm{it}} \quad = \quad \beta_i + \sum_{j=2}^{k} \beta_j X_{ijt} + \partial_{\mathrm{t}} + \mu_{\mathrm{it}} \qquad ----(3.21)$$

Where: $\mu_{it} = \sigma_{\mathrm{i}} + \mathrm{E}_{\mathrm{it}}$. In this scenario, the unobserved effect is removed by subsuming it concerning the stochastic term. The second condition stated that the Zp variables are spread independently of all the X_j indicators. If this is not the case, σ and μ will not be uncorrelated with the X_j series, the random effects variables will be biased and inconsistent.

3.6.7 Panel Data and Generalised Methods of Moments (System GMM)

Panel data and system Generalised Methods of Moments (Sys-GMM) were employed in this study because they are dynamic data measurements suitable for this research. This is because the GMM controls endogeneity and simultaneity in the model. Panel data is considered longitudinal data containing multi-dimensional data used for measurement over a specific period. These data are characterized by multiple periods for the same entity, such as individuals, organisations, countries etc., as the case may be. The GMM controls the endogeneity of the lagged dependent variable in a dynamic model, primarily when there is a correlation between the explanatory variable and stochastic error term in the model (Arellano, 1986; Adeleye, 2018). Interestingly, system GMM curbs omitted estimates bias and undiscovered panel heterogeneity that may likely arise from the study's cross-country modelling. Suppose we have:

$$y = X'ß + u \ldots\ldots\ldots\ldots\ldots\ldots.3.22$$

Where y and u are N x 1 vectors: *ß* signifies K x 1 vector of unknown estimates: X denotes N x K matrix independent variables. Due to the assumption of Endogeneity stated earlier, it is assumed again that matrix Z indicates N x L, where L > K. Z components comprise a set of estimates highly correlated with X but orthogonal to the error term u (i.e., a group of valid instruments). That is to say, the Z matrix is said to comprise variables unrelated to the error term u.

3.7 CONDITIONS AND SITUATIONS FOR ADOPTING SYSTEM GENERALISED METHOD OF MOMENTS

The first circumstance for adopting GMM is using dynamic panel methods. Secondly, when the small T and large N are to be estimated in studying a group or panel data. Thirdly, in a situation where independent variables are not strictly exogenous, i.e., endogeneity exists in the specified model. This means that independent estimates' past and possibly present realization are correlated with the stochastic terms. That is, to ascertain whether present and past human capital skills and infrastructure development correlated with the error terms. Fourthly, when the model has an arbitrary distribution of fixed effects, GMM is adopted to address this inappropriate trend. Lastly, as it is pertinent to curb the presence of heteroscedasticity and autocorrelation in the groups, the GMM is employed to address these circumstances.

Some notable peculiarities of GMM: *N>T, i.e., the number of cross-sections must be greater than the time lag (span). The model uses instrumental variables as an estimation, i.e. (IV) estimation. Instruments can be internal [gmmstyle ()] and external [ivstyle ()]. Instrument such as Z must be exogenous to error term (u), i.e., E (Z'u) = 0, and the number of Z instruments must be ≤ Number of cross*-section, *N. Note: According to STATA, variable(s) that fall with the brackets [gmmstyle ()] and [ivstyle () are internal and external instruments respectively.*

3.8 ALIGNING THE RESEARCH OBJECTIVES WITH THE EMPIRICAL TECHNIQUES/METHODS FOR ANALYSIS

Investigating the factors determining industrial output growth (IDO): Trends and System–GMM analysis were adopted to ascertain general factors' effects on IDO. This technique disclosed how the endogenous nature of human capital skills and infrastructure influence industrial output growth in SSA using disaggregated short-run and long-run system GMM.	**Empirical Modeling:** $\boldsymbol{LogIDO_{i,t} = \beta_0 + \beta_1 logGCF_{i,t} + \beta_2 logAYS_{i,t} + \beta_3 LPR_{i,t} + \beta_4 logLBF_{i,t} + \beta_5 LIR_{i,t} + \beta_6 SER_{i,t} + \beta_7 HOC_{i,t} + \beta_6 LogACE_{i,t} + \beta_7 logACT_{i,t} + \beta_8 logICT_{i,t} + \beta_9 LogAWP_{i,t} + u_{i,t}}$ Instrumental estimates $\boldsymbol{\beta_{10} logGERs_{i,t} + \beta_{11} LER_{i,t} + \beta_{12} GERt_{i,t}}$ *(See the expanded model in a chapter for the meaning of abbreviations. See also under 3.3.6, Appendix 1 for the meanings of the Abbreviations)*

Examining the comparative effects of Human Capital skill and Infrastructure on industrial output growth (IDO) across sub-regional blocs in SSA: sub-sample and FE-LSDV techniques were adopted to compare different sub-regional effects of human capital skill development and infrastructural development on industrial sector growth. This addresses the lack of knowledge on prioritising human capital development and infrastructure development for industrial sector growth within sub-regional economic blocs. *(Please see under sub-section 3.3.6)*	<u>Model 1</u>: Variables for Human Capital Skills Development $LogIDO_{i,t} = \beta_0 + \beta_1 logAYS_{i,t} + \beta_2 logLPR_{Ei,t} + \beta_3 LogLBF + \beta_4 SER_{i,t} + \beta_5 LogHOC_{i,t} + u_{i,t}$ <u>Model 2</u>: Variables for infrastructural development. $LogIDO_{i,t} = \beta_0 + \beta_1 logACT_{i,t} + \beta_2 logICT_{Ei,t} + \beta_3 LogFDI + \beta_4 GCF_{i,t} + \beta_5 LogACE_{i,t} + u_{i,t}$ *(See the expanded model in Chapter 6. See also Appendix 2 for the meanings of the Abbreviations)*
Investigating the threshold and Asymmetric effects of human capital skills and infrastructure on IDO across sub-regional blocs in SSA. This study tried to ascertain two effects regimes across sub-regional nations in SSA. To achieve this, sub-Saharan countries were classified based on their economic blocs, such as ECOWAS, ECCAS, EAC and SADC, to ascertain regional-specific paired effects of human capital skills and infrastructure on industrial output for individual sub-region policy decisions towards improving industrial output growth (IDO). *(See also under sub-section Appendix)*	The threshold asymmetric via NARDL analysis: <u>Model 1</u>; $\triangle logIDO_i = \beta^0 + \sum_{j=1}^{p} \beta_1 \triangle logIDO_{i-1} + \sum_{j=0}^{p} ({\beta_2}^{+} logGCF^{+}{}_{i-1} + \cdots + u_{i,t}$ *(See expanded models and meaning of abbreviations in chapter 3)*

3.9 JARQUE-BERA TEST OF NORMALITY IN SMALL AND LARGE SAMPLES

The Jarque-Bera Test of Normality is an essential assumption of descriptive statistic test in regression analysis. Notably, the implication from the process depends upon the normality assumption(s) of the residuals within the Confidence intervals in which the Z/t-tests and F-tests would be valid, when the normality assumption was not violated. So, it is important to estimate whether the residuals are normally distributed. This is to determine if all the variables follow a normal distribution. Consequently, the hypothesis is formulated as Ho: The estimated variables that are normally distributed. Hi: The estimated variables that are not normally distributed.

Note: This Jarque-Bera statistic test is important in the study because it revealed the normality of the data employed in the study, particularly in a large number of (univariate) normality tests.

Also, the normal distribution is based on two properties, irrespective of what the parameters μ and σ, specified. There are major moments in achieving the Jarque-Bera statistic test. Firstly, the mean in the sample is used. Secondly, through the variance distribution in the sample. Thirdly, through the skewness, which estimates the degree of uniformity in the distribution. And lastly, the Kurtosis which estimates the height of the distribution curve from the mean.

Furthermore, the skewness in the sample distribution is expressed thus;

$$\widehat{\boldsymbol{Skewness}} = \frac{\frac{1}{n}\sum(Y_i - \bar{Y})^3}{\hat{\sigma}_Y{}^3}$$

Therefore,

Population	**Sample**
$\boldsymbol{Skewness} = \frac{[E(Y-\ \mu)^3]}{\sigma^3}$	$\widehat{\boldsymbol{Skewness}} = \frac{\frac{1}{n}\sum(Y_i - \bar{Y})^3}{\hat{\sigma}_Y{}^3}$

3.9.1 The Decision Rules in Skewness Statistical Measure

1) Suppose the outcome is Zero skewness. This means that there is asymmetric distribution i.e. T-distribution.
2) If the outcome is Positive skewness. This implies that the estimated variables are skewed to the right.
3) If the outcome is Negative skewness. This indicates the left long tail of the distribution, i.e. the distribution skewed to the left.

Consequently, the Kurtosis is;

$$\boldsymbol{Kurtosis} = \frac{E(Y-\ \mu)^4}{E(Y-\ \mu)^2]^2}$$

$$\boldsymbol{Kurtosis} = \frac{E(Y-\ \mu)^4}{(\sigma^2)^2}$$

The sample estimate of Kurtosis is:

$$\widehat{Kurtosis} = \frac{\frac{1}{n}\sum(Y - \bar{Y})^4}{(\sigma^2)^2}$$

Therefore,

Population	**Sample**
$Kurtosis = \frac{E(Y-\mu)^4}{E(Y-\mu)^2]^2}$	$\widehat{Kurtosis} = \frac{\frac{1}{n}\sum(Y-\bar{Y})^4}{(\sigma^2)^2}$

Note: When the normal distribution from the Kurtosis is 3, the measure (Kurtosis -3) is called "the Excess Kurtosis." That is**,**

$$Kurtosis = \frac{E(Y-\mu)^4}{E(Y-\mu)^2]^2} - 3$$

3.9.2 The Decision Rules in Kurtosis Statistical Measure

1) Suppose the outcome from the Kurtosis distribution is equal to 3, it is said to be mesokurtic.

2) If the outcome from the Kurtosis distribution is greater than 3, it is said to be leptokurtic (i.e. fat-tailed).

3) If the outcome from the Kurtosis distribution is less than 3, it is said to be platykurtic.

4) If the outcome from the Kurtosis distribution is zero, it means excess Kurtosis.

Note: Two statistical properties of the normal distribution are carried out in the Jarque-Bera test. That is, Normal distribution is assumed to be symmetric around its mean (when skewness is zero), and Normal distribution of kurtosis is assumed to be three (i.e. < 3, =3 or >3) or equal to excess kurtosis (i.e. when Kurtosis is zero).

3.9.3 Jarque-Bera Test Hypothesis

Consequently, the Jarque-Bera test hypothesis is specified; thus, Ho: The estimated Data is normally distributed. Ho: The estimated Data is normally distributed. Hi: The estimated Data is not normally distributed.

$$JB_{Test\ Statistic} = n\ [\frac{\widehat{Skewness}^2}{6} + \frac{(\widehat{Kurtosis} - 3)^2}{24}$$

Let $\boldsymbol{S = \widehat{Skewness}}$

And

$$\boldsymbol{K = \widehat{Kurtosis}}$$

Then

$$\boldsymbol{JB_{Test\ Statistic} - n\ [\frac{S^2}{6} + \frac{(K-3)^2}{24}]}$$

Assuming there is no outliers in the data employed in the study, it is pertinent to prove that the normal distribution for Skewness is S = 0. Meanwhile, the normal distribution for Kurtosis is K = 3. So, the Jarque-Bera test statistic is said to be

$$\boldsymbol{JB_{Test\ Statistic} = n\ [\frac{S^2}{6} + \frac{(K-3)^2}{24}] = JB_{Test\ Statistic} = n\ [\frac{0^2}{6} + \frac{(3-3)^2}{24}]}$$

$$\boldsymbol{JB_{Test\ Statistic} = 0}$$

Notably, if the JB value is zero, it is assumed to be a normal distribution without outliers in the dataset.

In conclusion, Skewness is determined by random variables. Similarly, Kurtosis is determined by random variables. While Jarque-Bera is a random variable itself. Notably, if the hypothesis of normality is attained (i.e. Ho), the test statistic is assumed to be asymptotical as the number increases with chi-squared distributed at 2 degrees of freedom (df). Meaning that;

$$\boldsymbol{JB_{Test\ Statistic} = n\ [\frac{S^2}{6} + \frac{(K-3)^2}{24}]}$$

$$\boldsymbol{JB_{Test\ Statistic} \sim \chi^2\ (2)}$$

$$\boldsymbol{JB_{Test\ Statistic} \sim\ {\chi^2}_2}$$

3.10 ALIGNING THE RESEARCH PROBLEMS, QUESTIONS, METHODOLOGY AND CONTRIBUTIONS

Higlighted Research Problems	Emerging Research Questions	Research Methodology & contributions
There is problem of identifying factors that determine industrial output growth via knowledge-based productive inputs and infrastructural technology for industrial growth in SSA.	What are the factors that determine industrial output growth in sub-Saharan Africa?	System-GMM was adopted to account for the effects of factors determining industrial sector growth in SSA. This method was adapted to address possible endogeneity and simultaneity problems in the study
The lack of knowledge on what to prioritize between human capital skill development and infrastructure development compromises industrial output growth.	How does comparative effect of human capital skill and infrastructure development affect industrial output growth across sub-regional economic blocs in SSA?	Comparative analysis via Sub-sample, FE-LSDV & GMM modelling were used to compare different specific effects of human capital skill development and infrastructural development on industrial output growth across the sub-regional economic blocs in SSA.
Poor blue prints guiding investors decisions in public infrastructure and human capital skills development has been a serious concern due lack of study on paired regimes effect of human capital skills and infrastructure on industrial output growth across individual SSA sub-regions.	How does threshold and asymmetric effects of human capital skills and infrastructural development affect industrial output growth in SSA's sub-regional blocs?	The panel threshold and NARDL techniques were adopted to disclose threshold trajetory & two regiimes of asymmetric effects on industrial output growth via human capital skills (HCSD)and infrastructure (INF) across sub-rgional blocs in SSA.

Source: (Researcher, 2023)

3.11 OVERALL CONTRIBUTIONS TO THE BODY OF KNOWLEDGE

This research made original contributions to the body of literature from the following perspectives thus: Firstly, this study has identified the problem of limited productive human capital skills that can drive a knowledge-based economy for industrial sector growth in sub-Saharan Africa. Hence, the study adopted short-run and long-run two-step System-GMM to examine the endogenous nature of human capital skills and measures of infrastructure along with other control factors to ascertain factors determining industrial output growth in SSA. The endogenous aspects of the analysis concisely link the theoretical framework to empirical modelling in the study. This method draws perspectives on how the cost-income-output dimensions of human capital skills and infrastructure advancement affect output. The pertinent factors needed to transform the current resource-endowed economies of the SSA countries into knowledge-driven economies for industrial sector growth were identified in the study. Notably, the two-step system GMM technique was adopted to pave the way for inclusiveness by estimating the significant impact of the factors across the four sub-regions in SSA. Hence, the study discloses the importance of implementing home-grown policy support for rapid industrial sector growth in SSA.

Secondly, the study addressed a lack of knowledge on what to prioritize between human capital skill development and infrastructural development regarding comparative effects on industrial output growth. Therefore, this study incorporates sub-sampling regression techniques, FE-LSDV comparative analysis, and confirmatory short-run and long-run system GMM techniques to account for the independent variable's effects that mainly affect industrial output growth. By disclosing sub-regional-specific effects and country-specific effects. Hence, these methods emphasised the need to expand industrial goods at the sub-region levels from the current narrow range of industrial goods across sub-regional blocs markets in SSA.

Thirdly, public goods like human capital skills acquisition, education, infrastructure, and output growth cannot be exclusively based on public decisions. Therefore, accounting for the different paired effects of human capital skills and infrastructure is pertinent to guide future investment decisions. The threshold and asymmetric paired effects disclosed how each indicator performs across individual sub-regions, making this study unique. With this approach, we could ascertain how the sub-regional economies can move from their current state of low industrial output growth to higher production by setting a threshold trajectory across SSA. Also, the two regimes of asymmetric effect were used to set the basis for investment in HCSD and INF across ECA ECCAS, ECOWAS and SADC groups of SSA countries. Panel threshold regression analysis and NARDL techniques were employed to establish the threshold and asymmetric effects of human capital skills and infrastructure on industrial output growth via individual countries, sub-regions and across SSA.
Lastly, the inability to prioritize investment in physical infrastructure with higher economic returns to scale on industrial sector growth is addressed. This study has classified infrastructure into major types: access to transportation, water, information technology and energy. Given this, trend and sub-sample analysis, short-run and long-run dynamic system-GMM modelling were evaluated to reveal individual effects of the infrastructure, where the degree of relationship between the

industrial output growth and economic returns to scale of each infrastructural was identified via robust regression of equality tests across SSA countries.

Other notable contributions: The study adapted and incorporated the five pillars guiding economic model building through the following, as echoed by Kutu and Ngalawa (2016) and Fonta and Ichoku (2003):

(i) The economic agent: the industries aiming to maximize output in SSA.

(ii) The environment where the model is built: the output functions that face the industries regarding demand and supply of factor inputs, government infrastructural interventions and regulations in SSA.

(iii) Choice of model: This study chooses the relevant endogenous models to be adopted to estimate industrial output growth in SSA.

(iv) Solution of the model: This study adapted augmented endogenous and collapsed Cobb-Douglas models based on economic intuitions to address emerging problems from the study.

(v) Model Analysis: This is to test the strength of the theoretical models built through empirical sub-sampling analysis, Fixed Effects Least Square Dummy Variables techniques and System-GMM analysis, panel threshold regression and Non-linear Autoregressive Distributed Lags (NARDL) to proffer possible way forward to the problem statements. Consequently, the modified models in the study accommodate opportunity cost through an average year of schooling and a conducive work environment through household consumption as factor influencing human capital skills development for industrial sector growth in SSA.

CHAPTER FOUR

FACTORS DETERMINING INDUSTRIAL OUTPUT GROWTH IN SSA

The main objective of this chapter is to address the first objective of the study, which is:

i) To examine factors determining industrial output growth in sub-Saharan Africa.

4.1 SUMMARY OF THIS CHAPTER

This study disclosed what factors determine industrial output growth in SSA. This is to identify the factors that significantly affect industrial output in SSA. Consequently, this study fills vacuums in the literature through the short-run and long-run system Generalised Methods of Moments (sys-GMM) to systematically investigate the factors that determine industrial output growth in SSA. Notably, the conventional sys-GMM technique was disaggregated into short-run and long-run to reveal how human capital skill development and infrastructure measures determined industrial output growth. Therefore, the study systemically disclosed diverse factors determining industrial output growth. The results from the sys-GMM demonstrated both short-run and long-run significant outcomes of the output growth determinants in SSA. Subsequently, the study recommended that countries in SSA should draft more sub-regional policy support toward redesigning and improving educational systems. By extension, the government should create a conducive learning environment to expedite modern skill acquisition that can attract growth in SSA. This would eventually promote knowledge-deepening toward a knowledge base economy in SSA to intensify modern human capital skills for improved general output growth. Lastly, there is a need to build the necessary institutions to sustain synergy between different industrial output growth indicators for improved industrial product variety.

4.2 INTRODUCTION

Human capital skills are productive inputs for industrial output growth (Becker, 1964; Branson & Leibbrandt, 2013). However, there are divergence views on how human capital skills along the measures of infrastructure affect industrial growth across sub-regional economies in sub-Saharan Africa (SSA), where low human capital skills, low technical skills, low creativity, low productive output, and low-value addition, among other factors, constrain industrial growth (Mendes, Bertella, and Teixeira, 2014; Rewat Thamma-Apiroam, 2015; Perepelkina, Perepelkinaa & Morozovaa, 2016; Obialor, 2017; Novignon & Lawanson, 2017; Akinlo, 2020; Ughulu, 2020; Keji, 2021; Ndaguba, & Hlotywa, 2021).

There are diverse output growth patterns across sub-regions in SSA. Hence, the study intends to identify factors determining industrial output growth in SSA. It first seeks to identify the determinants of skills and infrastructure on industrial output growth in SSA via the short and long-run system GMM. Consequently, this study would have addressed concerns about factors determining SSA's industrial output growth. The emerging questions are: firstly, which factor determines industrial output growth and to what extent in SSA? Industrial output growth requires highly improved human resources (Brunello & Rocco, 2017; Keji, 2021; Tadele, Sirany, & Nsiah, 2021; Githaiga & Kilong'i, 2023). Sub-Saharan Africa is constrained by limited human capital skills development in a way that affects industrial output growth. However, there is a need to grow the SSA's industrial sector through the diffusion of knowledge. Hence, this study is pertinent because it assesses how indicators of human capital potential influence growth in SSA (Wonyra, 2018; Akinlo, 2020).

In addition, the increasing demand for modern infrastructure networks to aid the production of high-quality goods has necessitated industrial output growth in SSA. It is important to note that physical capital, regarding infrastructure through the production process, is an imperative input for industrial advancement in the short and long run (Rebelo, 1991; Mankiw, 1995). However, the lack of commitment by the stakeholders in the realm of affairs has further promoted underinvestment in different infrastructural facilities, which might have caused slow industrial output growth in sub-Saharan Africa. Consequently, this has led to an increase in the cost of production and a reduction in value addition, particularly for finished goods in the sub-region, thereby reducing output growth in general. Investment in high returns on economic scale infrastructures such as electricity, ICT, railway, aviation facilities, road networks and housing, among others, are pertinent to expanding output growth. However, stakeholders have not prioritised investment in those physical infrastructures, which might likely influence industrial output growth against the poor state of industrial output growth in SSA (Fedderke & Bogetić, 2006).

Africa has a vast labour force, and a large proportion resides in the sub-Sahara Africa region (Akinola & Mbonigaba, 2019). Despite the vast residents of human capital and infrastructure in SSA, the number of skills these populace possess and infrastructural spread still fall short of catalyst industrial growth compared to North America, Europe and Asia (World Bank Development Index, 2021). However, SSA's slow growth, low productive strength, low human capital skill development, and poor infrastructural spread deserve urgent attention. Advancing human skills and infrastructure technology is strongly associated with higher output growth (Branson & Leibbrandt, 2013; Hung & Thanh, 2022). Since human capital skills are pertinent to increasing output, the ability to transform these skills across other factor inputs, such as infrastructure, can inform industrial output growth within SSA.

Recent data from the World Bank Development Index (2021) in Figures 1, 2, 3 and 4 revealed a sharp drop in output growth concerning determinants of output growth unit inputs and a sharp decrease in the value-added percentage in the production chain across SSA. This revelation contradicts the assumption of endogenous growth theory (Lucas, 1988; Romer & Weil, 1992; Rewat Thamma-Apiroam, 2015; Obialor, 2017; Novignon & Lawanson, 2017; Akinlo, 2020). Poor human capital skills development might be responsible for the vast gap between trends for output growth and human capital skill development indicators, which has resulted in low industrial output growth in SSA (Keji, 2021; Rumanzi et al., 2021). Possibly, the few sharp brains around the sub-region are not motivated for improved output growth, which had exposed them to brain drain.

In Figure 4.1, the brief background information on the cross-section of output growth in SSA was discussed: It is pragmatic that transverse selected cross-section of countries' economic units of output continuously nosedived throughout the periods under review. The salient lesson learnt from the schematic evidence is that countries' output growth generally dropped drastically in recent years, which is an implication for this study. Notably, data for industrial output growth from the selected countries such as Angola (An-OTG), Benin (Be-OTG), Botswana (Bot-OTG), Equatorial Guinea (Equ-OTG) and Gabon (Gab-OTG) showed a recent decline in general output growth in the region. Also, the cross-section of productive output growth among the selected SSA countries in recent years remained below the expected range, as indicated in Figure 4.1.

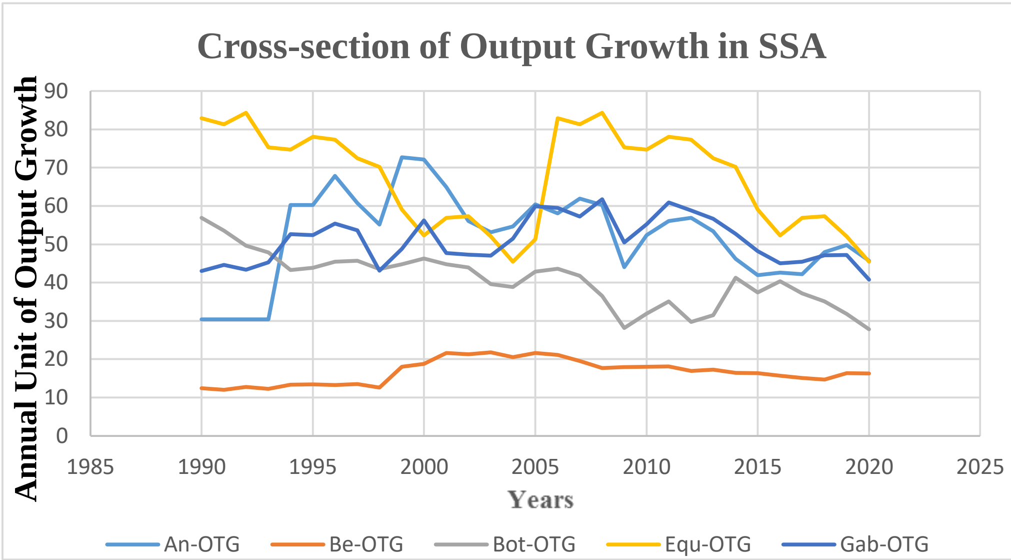


Figure 4.1: Cross-section of Output Growth in Sub-Sahara Africa

Source: Adapted from the World Bank Development Index (2022).

In Figure 4.2, the brief background information on human capital populace vs. output growth was discussed. Evidence suggested low output growth, particularly between 2015 and 2020, and the human capital size regarding population growth rose without a significant increase in output growth. The trend for industrial output growth further nosedived during the same periods (Adeosun & Popogbe, 2020). This evidence contradicts the neoclassical theory assumption of a direct link between a rise in human capital as a factor input and unit of output growth. That is, output growth is caused by a rise in human capital potential as a unit of input (Solow & Swan, 1956; Mankiw, Romer, and Weil, 1992; Lucas, 2002; Keji, 2021).

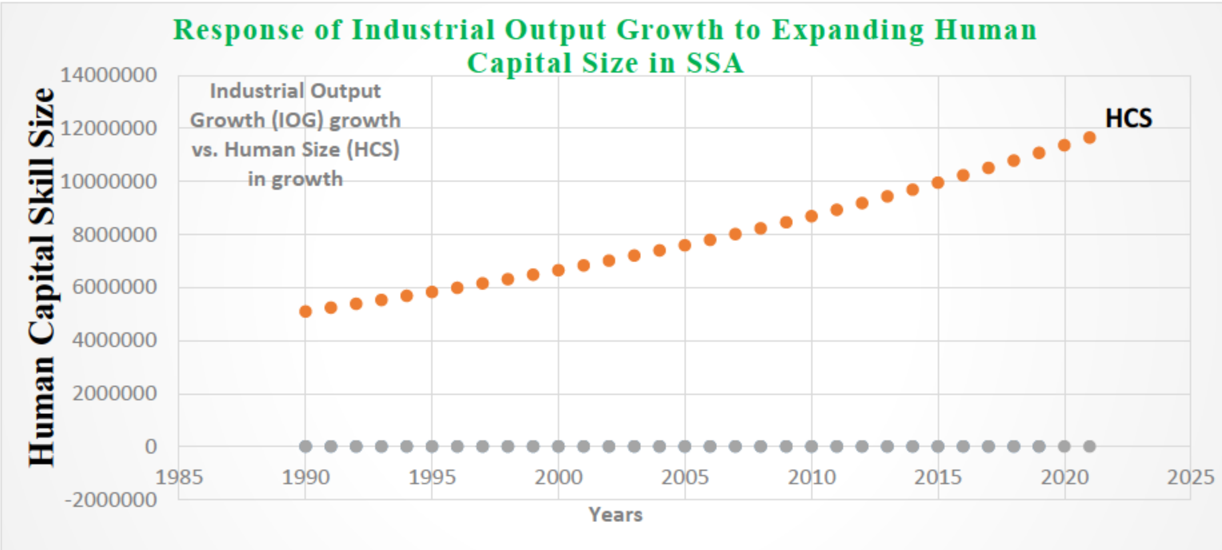


Figure 4.2: Response of Industrial Output Growth to Expanding Human Capital Size in SSA

Source: Adapted from the World Bank Development Index (2022).

In Figure 4.3, the brief background information on the configuration of inter-regional infrastructure was discussed: Figure 4.3 reveals the comparative rank of the cross-region spread of infrastructure in the last decade. Figure 4.3 displayed that SSA's performance regarding factor inputs, such as infrastructure for output growth, was low compared to other regions. Therefore, it is evident that nations in SSA lack the requisite infrastructure in access to communication, road networks and energy to drive industrial growth. Notably, most sub-regional governments in sub-Saharan Africa have made little or no concerted effort to identify and correct gaps in infrastructural investments for industrial output growth. Ludé and Thérèse (2020) emphasised that the roles of governance in public infrastructure investment cannot be over-emphasised due to its publicness, which is an implication of this study.

Similarly, Sultana, Rahman and Chowdhury (2012), Emily and Muyengwa (2021), and Shahrivar, Mahmoodian and Li (2022) stressed that maintenance of critical infrastructures is pertinent for output growth. Infrastructural maintenance can be in the form of performance-based contracting. This strategic approach can address most challenges facing infrastructural development across

SSA countries. In the meantime, past studies revealed diverse conclusions and could not ascertain the long-run effect of infrastructure investment on industrial output growth. For instance, related studies by Abdurraheem and Naim (2018), Keji and Efuntade (2020), Abdulqadir and Asongu (2022) and Du et al. (2022) suggested that infrastructural tech development propels productivity growth. Whereas studies by Gukat and Ogboru (2017), Okumoko et al. (2018) and Bennett et al. (2015) posited that public investment in infrastructure has a negative and insignificant influence on output growth using Autoregressive Distributed Lags, Ordinary Least Square (OLS), among other likely biased estimates.

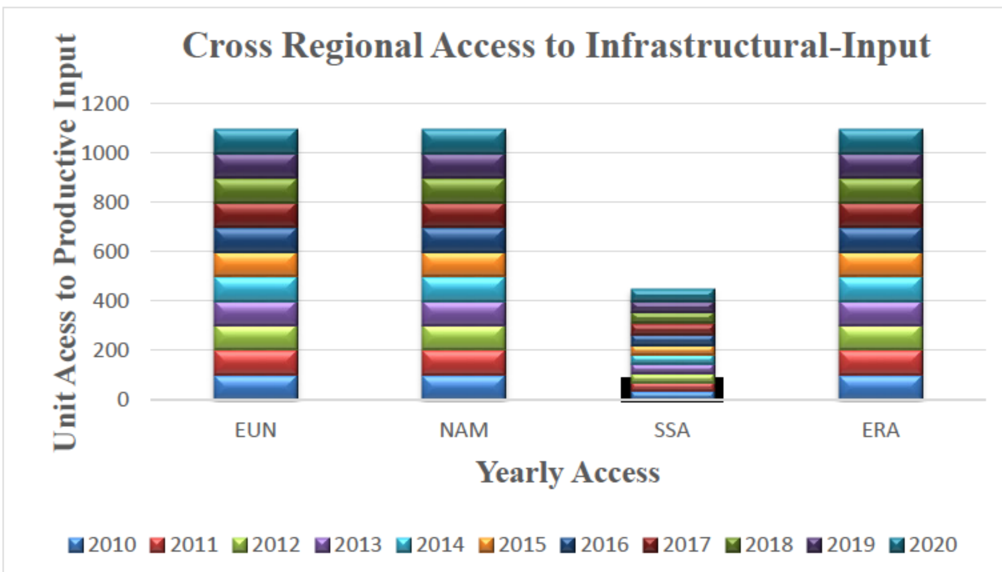


Figure 4.3: Configuration of Inter-Regional Infrastructure

Source: Adapted from World Bank Development Index, (2023).

Figure 4.3, which cuts across various regions like Euro-Area (ERA), European Union (EUN), and North American Euro (NAM), has exposed that sub-Saharan (SSA) lags behind other regions regarding infrastructure spread toward productivity growth.

Figure 4.4 unravels the economic pattern in SSA and shows the historical trends of value-added production units as the proxy for industrial output growth across SSA countries. The schematic evidence disclosed that SSA's average output growth continues to nosedive throughout the period under review, mainly from the eve of 2005 to the start of 2022. Given this, it is pertinent to investigate why the sub-region industrial output growth continues to drop over time and how this can be addressed through proactive sub-regional policy support.

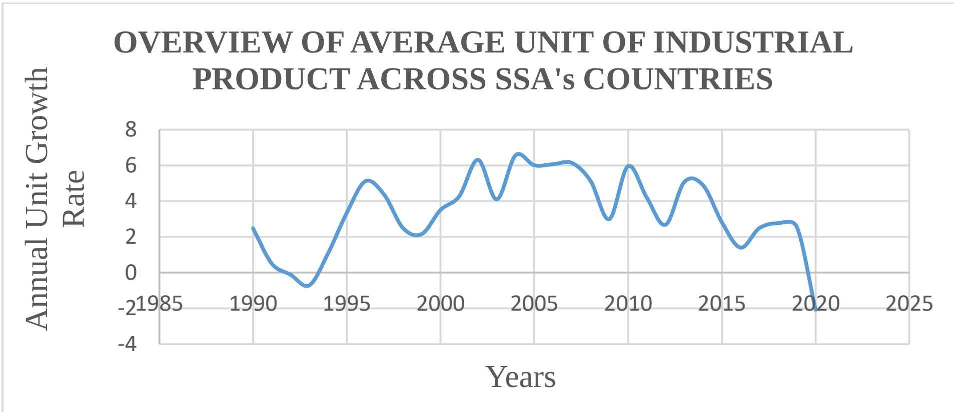


Figure 4.4: Overview of Average Unit of Industrial Product across SSA's Countries

Source: Adapted from the World Bank Development Index (2021)

Consequently, emerging evidence showed the trends analysis in Figures 4.1, 4.2, 4.3 and 4.4. There was low industrial output growth and poor human capital skills advancement and infrastructure spread, among other factor inputs in SSA compared to other regions like the Euro-Area (ERA), European Union (EUN), and North America (NAM). The case of SSA contradicts the neoclassical theory's assumption of a direct link between human capital skills input and unit of industrial output growth (Solow & Swan, 1956; Mankiw, Romer, & Weil, 1992; Keji, 2021; Githaiga & Kilong'I, 2023). Due to the recent global outbreak, this study is pertinent during this belt-tightening period among developing economies. Therefore, focusing on factors determining SSA's industrial output growth is pertinent.

On this note, the rest of the study is grouped into different sections. Section two comprises the literature and theoretical reviews. The previous chapter, i.e., chapter three, described the model building and methodology. In the meantime, the next is to explain the empirical findings and the conclusion and recommendations from the study.

4.3 THE METHODOLOGY FOR THE FIRST OBJECTIVE

The extant endogenous output growth theory is adopted in the study to ascertain the determinants of industrial output growth as a pre-condition for the first objective of the study. As advocated by Arrow (1962) and Lucas (1988) in Romer (1994) and Lucas (2002), they emphasised different determinants of output growth and how sustainable these investments in those factors, such as human capital, propel output growth compared to investment in physical capital. Mankiw (1992) and Romer (1994), therefore, introduced stock knowledge in human capital as the public stock for general output growth to come up with:

This model 3.9iv in chapter three has been transformed to become econometric model 4.1 to commence empirical analysis to achieve the first objective of the study.

; $\boldsymbol{logy*_{i,t} = a_{i,t} + \Phi h_{i,t} + \gamma logk_{i,t}} \dots \mathbf{4.1}.$

Model 3.9iv in chapter three, expressed indicators of human capital skill and infrastructure as causal of industrial output (y*) function. Moreover, to achieve our main first specific objective, human capital skill is proxy as h subscripts (i,t), infrastructure is proxy as k subscripts (i,t) and industrial output is expressed as y* subscript (i,t) (i.e. human capital is determined from the output dimension) to supply along infrastructure and consumption of human capital efforts across the selected countries were being accounted for. U subscript (i,t) explains other stochastic factors determining output growth, Φ and γ symbolize slopes of the factor estimates and 'a' signals the constant. k subscript (i,t) is further expanded along with additional key and control factors such as cost of infrastructure, education, school enrolment, exchange rate, access to transport, access to energy, ICT, inflation rate, average time spent in school (which account for an opportunity as part of cost dimension). Also, education outcomes, health outcomes, literacy rate, labour participation rate, and life expectancy contribute to SSA's human capital dynamics.

Furthermore, this paper certainly adopted panel estimation of the sub-sample and system Generalised Method of Moment (Sys-GMM): These techniques would change the static model 4.0 to dynamic model 4.1 to disclose how the determinants of some of the indicators for human capital and infrastructure influence industrial output growth in SSA. Therefore, this approach shall answer the emerging problems of low productive skills and slow industrial output growth in SSA. Therefore, the initial econometric system GMM model is specified thus:

$$\boldsymbol{Logy}*_{\boldsymbol{it}} = \beta\boldsymbol{Logy}*_{\boldsymbol{it-1}} + \boldsymbol{\Phi h_{it}} + \boldsymbol{\gamma logk_{i,t}} + \boldsymbol{\gamma Z'_{it}} + \eta_{\boldsymbol{i}} + \eta_{\boldsymbol{t}} + \boldsymbol{u_{it}} \text{.....}\mathbf{4.2}$$

Where,

The dynamic model was formed from 4.0, and the constant "a" was absorbed. Log y* is the dependent variable that captures industrial output growth (IDO), lag of y* explains the previous year's output growth (IDO), h is disaggregated to capture all the determining variables of human capital skill development (such as SER LIR LPR LER LBF), k is disaggregated to capture all the determining variables of infrastructure development(such as ACE ACT ICT AWP), Z' is the vector of control variables (such as GCF FDI AYS HOC), while the $\eta_{\boldsymbol{i}}$ explains unobserved cross-country-specific effects while $\eta_{\boldsymbol{t}}$ **d**enotes the time trend in the respective country. i captures several countries to be estimated, t is the number time series, $\boldsymbol{\Phi}$**,** $\boldsymbol{\beta}_1$**,** and $\boldsymbol{\gamma}$ parameter coefficients for each independent variable, and u explains the stochastic error time. The inclusion of the control variable is to ascertain whether the dynamics of factors influencing industrial output growth indeed hold after considering some indicators' endogenous and dynamic natures. Hence, the study adopted a dynamic model via sys-GMM to capture continuous change in factors of measurements, to address measurement error, to curb omitted variable bias, to address endogeneity problems that may likely arise (Arellano & Bond, 1991; Arellano & Bover, 1995; Blundell & Bond, 1998; Adeleye, Osabuohien and Bowale 2017). The study employed the Hansen/Sargan test to ascertain the over-identifying and validity of the instruments.

Expanding by introducing key and control variables for h and k in model 4.1 and replacing y* with IDO;

$$\begin{aligned}\boldsymbol{logIDO}*_{\boldsymbol{i,t}} = {} & \beta\boldsymbol{Logy}*_{\boldsymbol{it-1}} + \boldsymbol{\Phi}\left[SER_{i,t} + LIR_{i,t} + LPR_{i,t} + LER_{i,t} + logLBF_{i,t}\right]_{\boldsymbol{i,t}} + \boldsymbol{\gamma}[ACE_{i,t} \\ & + ACT_{i,t} + ICT_{i,t} + AWP_{i,t}] + \alpha_1\boldsymbol{AYS} + \boldsymbol{\alpha_2 HOC} + \alpha_3\boldsymbol{GCF} \\ & + \alpha_4\boldsymbol{FDI} + \boldsymbol{u_{it}} \ldots\ \mathbf{4.3}\end{aligned}$$

Note: *Log signs were dropped from variables already in rates and percentages to avoid double logging and unnecessary loss of numbers.*

4.4 PRE-ESTIMATING ANALYSIS FOR THE STUDY

The First Generation UNIT ROOT- IPS

This study conducted all the necessary pre-estimation tests to avoid biased estimates. Pre-estimating techniques such as panel unit root test for cross-section dependence and breaks via Im-Pesaran-Shin-IPS and Karavias and Tzavalis (2014) tests. Im-Pesaran-Shin-IPS (1997 and 2003) and Karavias and Tzavalis (2014) tests are pertinent to unravelling the presence of panel unit root across the first and second-generation tests for cross-sectional dependence and structural breaks. For the fact that IPS and Karavias and Tzavalis (2014) were efficient tools for detecting cross-section dependence and structural breaks in panel data, the adoption of IPS and Karavias and Tzavalis (2014) in the study rested on the fact that N>T, i.e. the number of cross-sectional entity N is greater than the time T. Notably, other justifications for IPS and Pesaran were well elaborated in the previous section. Given this, IPS is first carried out to ascertain whether the panel data has unit root and cross-section dependence. This is premised on the assumption that Ho: All panels contain unit roots. Ha: Some panels are stationary. The number of panels is 40, and the number of periods is 32. Two optimal lags were employed via ADF regressions. Under this condition, xtunitroot was used to estimate the IPS Wt-bar statistic asymptotically and normally distributed when T and N are reasonably large. IPS requires many periods and panels to be used in this test.

Table 4.1: **IPS-Unit Root**

Variables	**Statistic**	**P-value**
LogIDO	-1.8380	0.0330
SER	-13.2316	0.0000
LPR	-2.7563	0.0029
logLBF	-3.4808	0.0002
AYS	-2.1050	0.0176
HOC	-9.5359	0.0000
LIR	-6.4809	0.0000
LER	-32.7711	0.0000
GCF	-17.8436	0.0000
FDI	-5.7405	0.0000
ICT	-7.7889	0.0000
ACE	-11.9585	0.0000
ACT	-2.3555	0.0092
AWP	-2.3334	0.0121

Source: *Authors computation (2023)***. Note:** *Data were adapted from the World Bank data, 2023.* **Also,** *some "log" notations were removed from variables already in the rate. LogIDO=Log of Industrial Output, SER=School Enrolment Rate, LPR=Labour Participation Rate, LogLBF=Log* *of Labour Force, AYS=Average Years of Schooling, HOC=Household Consumption, LIR=Literacy Rate, LER=Life Expectancy Rate, GCF=Gross Capital Formation, FFDI=Foreign Direct Investment, ICT=Information Technology, ACE=Access to Energy, ACT=Access to Transportation and AWP=Access to water resources. That data were drawn across forty SSA countries. The countries were coded as c-id, which implies country Identity: Angola =1, Benin =2, Botswana =3, Burkina Faso =4, Burundi =5, Cabo Verde =6, Cameroon =7, Chad =8, Comoros =9, Congo, Dem. Rep. =10, Congo, Rep. =11, Cote d'Ivoire =12, Equatorial Guinea =13, Eritrea =14, Eswatini =15, Ethiopia =16, Gabon =17, Gambia, The =18, Ghana =19, Guinea =20, Guinea-Bissau =21, Kenya =22, Lesotho =23, Madagascar =24, Mali =25, Mauritania =26, Mauritius =27, Mozambique =28, Namibia =29, Niger =30, Nigeria =31, Rwanda =32, Senegal =33, Sierra Leone =34, Sudan =36, Tanzania =37, Togo =38, Uganda =39, and Zimbabwe =40.*

Based on the inferences drawn from the IPS unit root tests in Table 4, the panel data drawn from the World Development Index, the International Labour Organisation and the World Bank were stationary to reject the null hypothesis that the panel model contains a unit root. The IPS results disclosed that the key variables were statistically significant, meaning the panel series were stationary over time without cross-sectional dependence. The significance levels vary across the variables, as disclosed in Table 4. For example, the dependent variable of logIDO, LPR, AYS, ACT and AWP were stationary at five per cent, while indicators for SER, logLBF, HOC, LIR, LER GCF, FDI, ICT and ACE were statistically significant at one per cent to reject the null hypothesis of unit root in the panel data. Hence, there was no cross-sectional dependence in the panel data.

The Second Generation UNIT ROOT- Pesaran

Leveraging the benefits of the second-generation version of unit root tests for ascertaining possible cross-section dependence (CSD) in panel data analysis, this study improved the possible presence of cross-section dependence through the CSD test. This new generation of unit root tests eases the cross-sectional independence assumption through a standard factor model (Hurlin & Mignony, 2006). Pesaran (2003) suggested an alternate way to address the problem of cross-sectional dependence in panel data estimation. Pesaran forwarded an/a-factor model with heterogeneous filling factors for the residuals. However, instead of resting the unit root estimation on deviations form to calculate estimates, he augmented-Dickey-Fuller models with the cross-section mean of lagged levels and first differences in individual series.

Table 4.2: **Pesaran CD Unit Root**

Variables	Cross Dependence test	P-value
D.LogIdo	8.51	0.016
D.SER	31.94	0.000
D.LPR	7.23	0.000
D.LogLBF	152.92	0.000
D.AYS	2.87	0.009
D.HOC	7.32	0.000
D.LIR	19.15	0.000
D.LER	123.37	0.000
D.GCF	2.85	0.004
D.FDI	22.00	0.000
D.ICT	45.48	0.000
D.ACE	118.65	0.000
D.ACT	17.15	0.000
D.AWP	8.01	0.0014

Source: *Authors computation, (2023).*

It can be recalled that Ho: indicated the null hypothesis that there is no cross-sectional dependence in the panel data, while Hi: implied the alternative hypothesis that there is cross-sectional dependence in the panel data. Based on the outcomes in Table 4.0, it can be observed that no case of cross-section dependence was reported. Consequently, the Ho benchmark under the decision rule is accepted at 5% and 1% significant levels, respectively. The alternative hypothesis is therefore rejected. There is no cross-sectional dependence affecting the industrial output and factors measuring human capital skills and infrastructure across SSA countries.

The Second Generation PANEL UNIT ROOT-Evidence of no BREAKS effects

This study adopted Karavias and Tzavalis (2014) to estimate the possible influence of structural break(s) in the panel data unit root. This is to ascertain whether known and unknown breaks can disrupt the panel cross-section flow (Karavias & Tzavalis, 2019). The motive behind this test was to avoid unbiased estimates in the study. This is encompassing and estimated via linear trends, cross-sectional heteroskedasticity and dependence, and non-normal errors. Stata's xtbunitroot was employed to actualise this process, as Karavias and Tzavalis (2014) suggested, which was adopted for panel-data unit-root tests with structural breaks. The method allows for more than one break in the panel data. The null hypothesis of all the panel time series possessed unit root, i.e. Ho: All panel time series are unit root processed, was drawn against the alternate hypothesis of some or all the panel series possessed stationarity, i.e. Hi: Some or all of the panel time series are stationary processes. This step is efficient and relevant to the study because panel data drawn from forty sub-Saharan countries were carefully estimated thus:

Table 4.3: **Unit Root for Breaks Effects**

Variables	Statistic	Bootstrap critical-value	P-value
LogIdo	-9.1348	-5.5099	0.0000
SER	-2.7953	-0.9966	0.0400
LPR	-1.0999	-2.1000	0.0040
LogLBF	-6.9830	-3.8665	0.0020
AYS	-17.1739	-0.0751	0.0031
HOC	-49.6544	-15.8063	0.0000
LIR	-16.6890	-5.7886	0.0000
LER	-2.2242	-1.0298	0.0500
GCF	-65.7383	-13.5994	0.0000
FDI	-30.3357	-5.8664	0.0000
ICT	-0.6750	-1.2900	0.0330
ACE	-15.2408	-5.3829	0.0000
ACT	-13.4385	-7.2112	0.0490
AWP	-53.3642	-1.7728	0.0000

Source: *Authors computation, (2023).*

Based on the inferences drawn in Table 4.1, it can be established that the null hypothesis of unit root with structural break effects in the panel data is rejected. It can be observed that each of the series in the panel data possessed stationary at the conventional levels of one per cent and five per cent, respectively, without noticeable structural break effects. The assumption that all panel time series are unit root processed did not hold, so the xtbunitroot command was applied. Hence, the statistics coefficient must be less than the Bootstrap critical value to reject the null hypothesis, as suggested by Karavias and Tzavalis (2014; 2019). It can be observed from Table 4.1 that all the series in the panel data possessed no unit root with no break effects based on the evidence from the statistics and Bootstrap critical value. For example, the statistics value for LogIdo at -9.1348 is less than the Bootstrap critical value of -5.5099, indicating no evidence of breaks effects in the panel series. The probability value was reported as 0.0000, which implied that the null hypothesis was rejected at the 1% significance level. The SER and LER statistics reported statistical significance at 5% levels of -2.7953 and -2.2242 with Bootstrap critical value of -0.9966 and -1.0298, respectively. The probability reported values at 0.0400 and 0.0500, indicating 5% significant levels for SER and LER with no unit root and break effects among the series in the panel data.

4.5 EMPIRICAL DATA ANALYSIS AND RESULTS

Data Statistics and Apriori Expectations for Objective One

The data for the factors determining industrial output growth were drawn from the World Development Indicators, a database of the World Bank 2022. These data are widely used, and maybe it is because of their accessibility and computability that they are in line with inter-regional empirical analysis. However, we have not ruled out the limitations to the accessibility of some data via the World Bank data, but it is still a better forum to source data for a study of this nature that concerns cross-country analysis (Adeleye, 2018). Data for industrial output growth is the dependent variable, while data for school enrolment rate, labour participation rate, and information technology were proxies as independent variables. Data for *household consumption* and *average years of schooling* are inserted as control and internal instruments. At the same time, *literacy* and *life expectancy* indicators were used as both direct factors and instrument indicators for industrial output. *Foreign direct investment* and *gross capital formation* data were injected as external control variables of productive input. On the a priori expectation, according to economic intuition, as posited in the endogenous model, a unit rise in school enrolment, labour participation rate, and composition of labour are expected to influence a unit increase in output c growth. This assumption was premised that the improved skill of an individual associated with a formidable infrastructure would increase his/her productive input, increasing the overall output level. Notably, details of justification for each indicator have been explained in the previous section, while we disclose the summary statistic and a priori expectation thus.

4.5.1 Overall Descriptive Statistics

4.5.1.1 Jarque-Bera Test of Normality

Notably, the inference from this process depends on the normality assumptions of the residuals within the Confidence intervals, which the Z/t-tests and F-tests validated when the normality assumption was not violated in the study.

4.5.1.2 Justification for Jarque-Bera Test of Normality in the Study

Firstly, it is to verify the assumption of normal distribution where there is no presence of outliers in the dataset. Secondly, it is to improve model performance in the analysis. Thirdly, it ensures the robustness of the statistics set for econometric analysis.

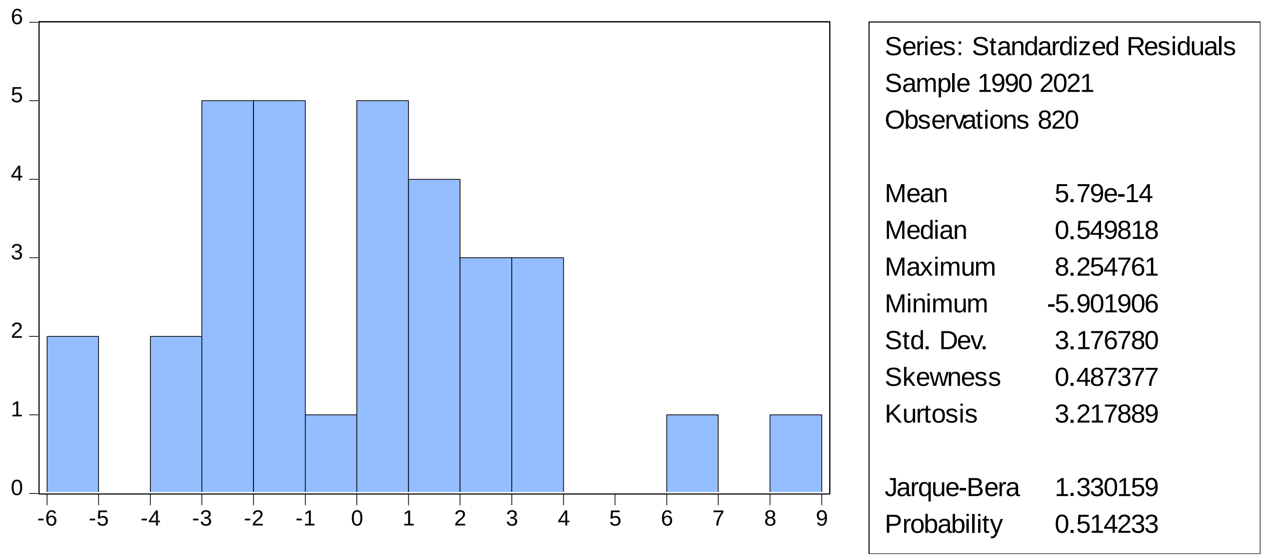


Figure 4.5: Normality Test

Source: *Authors Computation, (2023)*

Assuming there are no outliers in the data employed, it is pertinent to prove that the normal distribution for Skewness is S = 0. Meanwhile, the normal distribution for Kurtosis is K = 3. Recall that if the JB value is zero, it is assumed to be a normal distribution without outliers in the dataset. It can observed from Figure 4.5 that the null hypothesis of the Jarque-Bera (JB) statistic can not be rejected. The implication is that the dataset in the study is normally distributed around the mean. Similarly, the probability value at 0.514233 revealed that the JB statistics is greater than the 0.5%

conventional level. That is, the multiple of 0.514233 with 100 is about 51.4%, which is much greater than 0.5%.

Also, the figures from Skewness and Kurtosis justified the normal distribution of the dataset. Notably, the Skewness coefficient is positively skewed. Meanwhile, the Kurtoisi leptokurtic (i.e. fat-tailed) at 3.217889. The standard deviation disclosed the level of variance from the mean at 3.176780, which was too far from the mean. The implication is that issues of variables with outliers among the series are not dominant.

Table 4.4: **Descriptive Statistics of the Determinants of Industrial Output Growth**

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Apriori Expectation**
IDO	25.5595	13.3592	4.5559	84.3492	N/A
IDO (-1)	25.5233	13.4239	4.5559	84.3492	Positive
SER	0.8834	0.1507	-0.0536	1.4827	Positive
AYS	6.2766	0.7517	5.0000	8.0000	Positive
LPR	68.4893	11.7345	42.3900	92.1600	Positive
GCF	9.8052	30.1733	-18.7722	507.953	Positive
FDI	3.3489	7.8215	-26.6384	161.824	Positive
HOC	5.6536	18.6308	-46.9188	459.206	Positive
LIR	59.3713	22.0793	0.0000	101.473	Positive
LER	56.4236	7.2119	26.172	74.5146	Positive
ICT	2.2722	4.6449	0	37.6405	Positive
ACE	36.6379	24.6640	0.5339	100	Positive
ACT	20.7261	15.8749	0.1258	79.4936	Positive
AYS	6.2781	0.7539	5	8	Positive
AWP	43.4640	71.3940	0.4148	761.1115	Positive

Source: *Authors Computation, (2023).*

From Table 4.4, a quick look at the table shows that household consumption data has minimum statistics throughout the years. While 507.953, 459.206 and 161.824 were accounted for by gross capital formation, household consumption and foreign direct investment were high, respectively. Also, the index for school enrolment and average years of schooling move near the mean at 0.1507 and 0.7517 with minimum standard errors. At the same time, the literacy rate has the highest mean, i.e. the highest height (kurtosis curve), trailed by the life expectancy rate. Information technology and access to energy move nearer to the minimum than the maximum mean throughout the period under review.

Table 4.5 informs us of the possible association-ship between the dependent and independent variables. However, the negative and weak correlation outcomes among the series justify our arguments under the background problems, reflecting the situation concerning poor output growth in SSA. Industrial output exhibited a positive correlation with school enrolment rate. On the contrary, among the nine regressors, indicators for average years of schooling, labour participation rate, labour force, and gross capital formation disclosed a negative correlation with output growth. This might be connected with various dynamic effects of low productive skills and poor infrastructural spread in sub-Saharan Africa. Interestingly, the correlation coefficient among the independent variables is positive and negative but primarily weak, meaning that the data are free from the potential incidence of multicollinearity. However, indicators for access to water (AWP) and household consumption (HOC) disclosed high correlation coefficients, and they were dropped in the cause of the analysis. This was to improve the empirical outcome of the study.

Table 4.5: **Correlation Matrix of Determining Factors and Output Growth Indicator**

Var	IDO	SER	LPR	LBF	LIR	GCF	FDI	ICT	ACE	ACT	HOC	LER	AYS	AWP
IDO	1													
SER	0.04	1												
LPR	-0.09	-0.12	1											
LBF	-0.04	-0.07	0.155	1										
LIR	0.236	0.495	-0.01	-0.03	1									
GCF	-0.01	-0.02	0.045	-0.01	-0.08	1								
FDI	0.069	0.061	0.033	-0.05	0.044	0.119	1							
ICT	0.003	0.329	-0.22	-0.21	0.447	-0.06	-0.01	1						
ACE	0.143	0.365	-0.47	-0.05	0.46	-0.07	-0.038	0.638	1					
ACT	-0.17	0.011	0.143	0.411	0.025	0.04	0.157	-0.04	0.058	1				
HOC	-0.34	0.089	0.153	0.226	0.078	-0.01	-0.123	-0.21	-0.26	0.068	1			
LER	0.48	-0.11	0.044	0.009	0.17	0.019	0.071	-0.1	0.099	0.122	-0.18	1		
AYS	0.313	-0.04	-0.24	-0.21	-0.12	0.026	0.151	0.211	0.212	-0.13	-0.91	-0.09	1	
AWP	-0.31	0.044	0.236	0.212	0.124	-0.03	-0.151	-0.21	-0.21	0.13	0.906	0.087	-1	1

Source: Authors Computation, (2023). Note: Var denotes variables.

4.5.2 Empirical Results

It is pertinent for the study to estimate the factors that determine industrial output growth after the estimating in Tables 4.4 and 4.5 to ascertain the summary of statistics and correlation matrix of the factors that determine industrial output growth in SSA. The next is to conduct the short-run system GMM analysis.

Table 4.6: **Dynamic Short-Run Panel-Data Estimation, Two-Step System GMM** (Short-run robust model)

Number of instrument = 39	Number of observation = 1030	Wald chi2(10) = **6780.52** Prob> chi = 0.0000	Time variable = Years Obs per group: min= 24	Number of group = 40 avg = 25.75 max = 26
Variables				
LogIDO	**Co-efficient**	**Robust Standard Error**	**Z-statistics**	**Probability Value**
L1.logIDO	0.3149	0.1481	2.13	0.033
SER	-2.5577	0.7458	-3.43	0.001
AYS	-0.1737	0.0955	-1.82	0.069
LER	-0.0035	0.0067	-0.51	0.608
logLBF	0.0426	0.0232	1.84	0.066
GCF	0.0048	0.0019	2.49	0.013
FDI	0.0094	0.0039	2.44	0.015
HOC	-0.0005	0.0005	-0.08	0.933
LIR	0.0067	0.0026	2.59	0.010
LPR	0.0276	0.0119	2.32	0.020
ICT	-0.977	0.4394	-2.22	0.026
ACE	0.3128	0.0104	2.04	0.036
ACT	-0.4843	0.1518	-2.24	0.025
AWP	0.0077	0.0128	0.60	0.546
Con.	3.5080	1.1639	3.01	0.003

Source: *Authors Computation, (2023).*

4.5.3 Explanation of Empirical Results

The first row in Table 4.6 explains the nature and overall significance of the dynamic model estimation in the study. For instance, Wald statistics of 6780.52 and chi-square p-value of 0.000 showed the overall significance of the estimated results. At the same time, the Z-statistics explained the performance of individual variables concerning industrial output growth. Notably, the estimated factors influence industrial output growth in sub-Saharan African countries. Also, the first column for variables consists of the variable list, which discloses the level of interaction between the dependent variable (% of industrial added value) and the fourteen regressors expressed as coefficients, standard error, Z-statistics and probability value. Past output growth strongly determines SSA's current industrial output growth. This implies that industrial output growth is path-dependent, which indicates that the current level of a country's output growth strongly influences its future level of output growth.

Likewise, the school enrolment rate and average year of schooling are negative and statistically significant to influence output growth with p-values at (0.001) (0.069), which are less than one per cent and ten per cent levels of significance, respectively. A unit rise in the SER-school enrollment rate brings about 2.558 units to fall in industrial output at a one per cent significant level. This is an implication for proactive policy in the education sector across SSA. Also, a unit increase in AYS-average years of schooling brings about 0.174 units of fall in industrial output at a ten per cent significance level, contrary to the apriori expectation of positive association. Meanwhile, a unit rise in Loglbf-labour force causes a 4.3% rise in industrial output growth. The implication is that the increased ability to acquire needed skills effectively contributes to SSA's productive growth.

Similarly, a unit rise in GCF-gross capital formation brings about a 0.005 rise in industrial output growth at one per cent of significance. This implies that general domestic investment in the industrial sector was relatively low due to the marginal effect of 0.005 on output growth. Similarly, foreign direct investment in the industrial sector was relatively low across the SSA based on its marginal contribution to industrial output growth. For example, a unit rise in FDI- foreign direct investment brings about a 0.009 rise in industrial output growth at five per cent significant levels. Data for the LIR-literacy rate was statistically significant in determining industrial output growth in SSA. That is, a unit rise in the LIR-literacy rate brings about a 0.007 rise in industrial output growth at one per cent levels of significance. The implication is that the ability to communicate effectively contributes to a marginal increase in industrial output growth in SSA. LPR-labour participation rate was statistically significant at five per cent. A unit rise in LPR- labour participation rate brings about a 0.028 rise in industrial output growth at five per cent significant levels. Data for ICT-information technology was statistically significant at five per cent. A unit rise in ICT-information technology brings about a 0.977 fall in industrial output growth at five per cent significant levels. The implication is that the presence of basic technology needed to strive for synergy for improved output growth was low across industrial locations in SSA. This is due to poor technical progress in technological advancement via artificial intelligence applications, blockchain technology, machine and deep learning, programming and market automation, which were rare in SSA. Meanwhile, data for access to energy and transportation were statistically significant at five per cent levels. That is, a unit rise in ACE- access to energy brings about a 0.313 rise in industrial output growth at five per cent levels of significance, and a unit rise in ACT-access to transportation brings about a 0.484 fall in industrial output growth at five per cent levels of significant, respectively.

However, measures such as LER-life expectancy rate, HOC household consumption, and AWP access to water were not statistically significant in determining industrial output growth in SSA. Multicollinearity might be responsible for the insignificant outcomes of these variables in the short-run model. Hence, these data were dropped from the long-run system GMM statistical analysis.

4.5.4 General Empirical Implications

In the meantime, the economic implications of the GMM results are explained thus; for example, a unit increase in school enrolment rate and average year of schooling caused about -2.557668 and and-0.173741 fall in units of industrial output growth at 5% and 10% significant levels, respectively contradict the expected economic intuition, and this further reveals the current situation of slow output growth in SSA, as schooling system does not propelled industrial output growth. This is predated by skills mismatched with the inability to transform acquired skills toward improving output growth in SSA. Meanwhile, a unit rise in literacy and labour participation rates caused about 0.006689 and 0.027558 increases in output growth at 5% significant levels, respectively. This is an implication of poor productive skills possessed by stakeholders across the SSA industrial sector. Also, foreign direct investment and gross capital formation were statistically significant at 5 % levels, respectively. These control variables were better determinants of industrial output growth because they are pertinent to general investment via the location and localization of industries across the SSA.

Also, a critical look at the outcome of information technology showed that access to basic technology, such as the Internet, to aid productive activities falls short of propelling output growth. Consequently, this accounts for poor infrastructural conditions across SSA's country, affecting productive input. The crux of the matter is that poor motivation for necessities of life, such as a poor tech environment and obsolete work tools, affect productive growth. Other interactive terms, such as foreign direct investment and gross capital formation, positively and significantly impact output growth. This showed that the internalization of knowledge and general investment in the industrial sector are significantly different from zero. Therefore, cross-country location and localization of industries are crucial to the industrial output growth drive, and this needs to be encouraged among the SSA countries. Access to basic facilities such as energy and motor-able road networks promotes industrial output growth. In the case of SSA, there is still a vacuum in this regard as the contribution of accessible energy and transport to industrial output growth proved to be marginal with 0.312872 and 0.016988 unit inputs, respectively.

Some salient facts can be deduced from the empirical findings thus: Firstly, eleven of the fourteen indicators are significant determinants of industrial output growth, which means these variables are essential determinants of industrial output growth in SSA. Secondly, Wald statistic for the robust model disclosed the overall significance of our results in the short-run GMM model. Most key indicators were statistically significant in predicting current and future output growth across sub-Saharan Africa. Thirdly, a variable such as household consumption (HOC) is positive and insignificant in predicting output growth in the SSA, which means that household consumption is poorly improved in the SSA. This implication for the study might result from a poor welfare system regarding basic needs of life such as job insecurity, poor labour protectionist law and lack of motivation for on-job training. On this note, we need to perform post-estimation tests to show the validity of the short-run two-step dynamic system GMM results in Table 4.6. The autocorrelation and Hasen/Sargan tests were carried out, respectively, to ascertain the validity and reliability of the two-step dynamic system GMM model estimation in Tables 4.7 and 4.8.

Table 4.7: **Robust Arellano-Bond Autocorrelation Test**

Ho: No autocorrelation	
Arellano-Bond test for AR(1) z = -2.57	Pr > z = 0.007
Arellano-Bond test for AR(2) z = 1.37	Pr > z = 0.218

Source: Authors Computation, (2023).

Table 4.8: **Sargan/Hansen Test of Over-Identifying Restrictions**

Ho: Over-identifying restrictions are valid	
chi2(29)	= 34.70
Prob > chi2	= 0.215

Source: Authors Computation, (2023).

According to Roodman (2009), autocorrelation levels, as stated by the Arellano–Bond autocorrelation test, should be executed on the levels residuals rather than the differenced levels, which only apply to system GMM. Hence, the study built on this rule of econometric assumption. The salient fact from the second model is the fact that the presence of autocorrelation at the lower order is being corrected at the higher order; hence, the model is free from any incidence of autocorrelation (Arellano & Bover, 1995; Blundell & Bond, 1998; Adeleye et al., 2017 and Roodman, 2009; Akinola & Mbonigaba, 2019). Likewise, the Sargan test of over-identifying restrictions results was reported, which further implies that the Sargan test has a null hypothesis of "the instruments as a group is exogenous". The implication is that the higher the p-value from zero, the better the Sargan statistics (Sargan, 1958, cited in Roodman, 2009). Therefore, with the Sargan coefficient in Table 4.8, the Null hypothesis is rejected, stating that group instruments are strictly not exogenous, which means over-identifying restrictions are invalid. Hence, the GMM instruments employed in the study are excellent and free from adverse effects on the estimates.

Moreover, having established that measures of determinants have a short-run influence on industrial output growth in SSA using the short-run system GMM in Table 4.6, it is also pertinent to look at the long-run determinants of the factor inputs. According to the endogenous growth theory, the time factor is essential. Hence, this study considered the short-run and long-run influence on output growth.

4.6 LONG-RUN DYNAMIC EFFECTS OF DETERMINANTS OF INDUSTRIAL GROWTH, TWO-STEP SYSTEM GMM

It is worth noting that long-run analyses must be carried out only on the strong and significant determinants of short-run estimates, as this would reveal the level of consistent effects of the estimated variables in the model (Arellano & Bond, 1991; Arellano & Bover, 1995; Blundell & Bond, 1998; Adeleye et al., 2017 and Roodman, 2009). This forms part of the contribution to the extant empirical literature by estimating the statistical long-run influence of factors input on industrial output growth via the long-run system GMM. Notably, the key variables such as **SER, AYS, LogLBF, GCF, FDI, LIR, LPR, ICT, ACE and ACT** are statistically significant in the short-run dynamic model analysis, and they are the variables of interest under this section.

The long-run system GMM analysis relied on the following statistical computation and formula. That is, the long-run impact of human capital skill development on output growth for the η^{th} parameter effects is estimated by $\boldsymbol{\beta_\eta / [1 - \Phi]}$

Where $\boldsymbol{\beta_\eta}$ denotes the significant coefficient derived from the short-run system GMM estimate, $\boldsymbol{\Phi}$ explains the short-run coefficient of the GMM lag-dependent estimate. As stated above, statistical syntax divides the short-run coefficient estimate by one minus the short-run lag coefficient to compute the long-run coefficient estimate. Findings from Table 4.7 showed that all indicators of human capital skill development exhibit long-run effects on output growth in SSA. The variables for school enrolment, average year of schooling, and literacy rate demonstrated as sources of the former and informal means for knowledge acquisition were statistically significant regarding industrial output growth in SSA. *This is another contribution of the study to the empirical literature, as the study accounts for the transformation periods of endogenous skill, which is very rare among mainstream economic studies.* Details of relevant statistics reports such as Z- Z-statistics, probability value, and confidence level of the interval were disclosed in Table 4.9.

Table 4.9: Long-Run Dynamic Panel-Data Estimation, Two-Step System GMM (Specific Effects)

Statistics	Coefficient.	Std. Err.	Z statistics	P>|z|	95% Conf. Interval
SER	-3.7353	1.4603	-2.56	0.011	-6.5974 -0.8732
AYS	-0.2536	0.1636	-1.55	0.121	-0.5743 0.0671
GCF	0.0069	0.0036	1.96	0.050	-0.0004 0.0139
FDI	0.0137	0.0061	2.26	0.024	0.0019 0.0257
LIR	0.0098	0.0027	3.66	0.000	0.0045 0.0150
LPR	0.0402	0.0207	1.95	0.052	-0.0003 0.0807
LogLBF	0.0571	0.0364	1.57	0.117	-0.0142 0.1284
ICT	-3.5830	1.7816	-2.01	0.044	-7.0749 -0.0912
ACE	1.1473	0.5924	1.94	0.053	-0.0137 2.3084
ACT	-1.7761	0.8067	-2.20	0.028	-3.3572 -0.1951

Source: *Author's Computation (2023).*

Findings from Table 4.9 showed that most of the indicators determining industrial output growth in SSSA exhibited long-run influence. The variables for school enrolment as a source of the former or conventional means of knowledge acquisition continued to be negative and statistically significant on industrial output growth. However, the opportunity cost of skill acquisition proxy as average years of schooling is statistically insignificant in the long-run. The implication is that labour human capital cannot adjust to productive life in and out of school. Meanwhile, determining factors such as gross capital formation, foreign direct investment, literacy rate, labour participation rate, information technology, energy access and transportation were all statistically significant in the long run.

4.6.1 Long-Run Empirical Explanation

A unit rise in the SER-school enrollment rate brings about a 3.735 unit fall in industrial output at a five per cent significant level. This is an implication for proactive policy for education reform in SSA, as the negative influence of SER caused about a -3.735 unit drop in industrial output growth in the long-run. Meanwhile, a unit rise in LIR-literacy rate causes about a 0.009 rise in industrial output growth in the long-run. The implication is that increased ability to communicate effectively contributes to long-term productive growth across the SSA at a one per cent level of significance. Although LIR has a long-run positive impact on industrial output growth, the SSA government still needs a proactive approach towards improving literacy as its long-run contribution to industrial output growth seemed to be marginal at 0.009 unit input.

Meanwhile, average years of schooling-AYS is statistically insignificant in the long-run. That is, a unit rise in the number of years spent in school for further skill acquisition did not cause any unit rise in industrial output growth. The implication is that the opportunity cost of skill acquisition has adverse and insignificant effects on industrial output growth in SSA. Similarly, LPR exhibited some form of long-run significance at a ten per cent level. That is, a unit rise in labour participation rate caused about 0.040 units in industrial output growth. The implication is that human capital skills are pertinent to long-run industrial output growth in SSA.

Meanwhile, ICT disclosed a negative and significant influence on long-term industrial output growth. That is, a unit rise in information technology caused about 3.583 units to drop in industrial output growth, which implies poor infrastructural technology development across SSA. Similarly, ACT negatively and significantly influenced industrial output growth in SSA. That is, a unit rise in access to transportation caused about 1.776 units to fall in industrial output growth in SSA, contrary to the apriori expectation. This implies poor infrastructural spread in SSA and that more proactive measures must be implemented. However, ACE-access to energy conformed to economic intuitions. That is, a unit rise in access to energy brought about a 1.147 unit rise in industrial output growth across SSA.

Furthermore, control variables such as gross capital investment proxy as gross capital formation and variable for internalization of investment across countries' borders' proxy as a foreign direct investment were statistically significant in the long run. A unit rise in GCF and FDI brought about a 0.007 and 0.014 unit rise in industrial output growth, respectively. Here, the apriori expectation was fulfilled based on economic intuitions in the long-run.

4.7 CONCLUSIONS AND RECOMMENDATIONS

In an attempt to answer the research questions on how diverse determinants of factors inputs propelled industrial output growth in SSA. The study adopted descriptive statistics, correlation matrix, and two-step short-run and long-run system GMM methods to draw conclusions, which were rare among the mainstream studies. Subsequently, this research fills the current gaps by assessing the regional determinants and factors influencing industrial output growth in SSA. Therefore, the researchers contribute to the body of literature by providing evidence of the significant strength of the key determinant across SSA. Also, disaggregated system-GMM methods were used to ascertain the short-run and long-run effects of the factors determining industrial output growth. Hence, the study concludes that some key determinants negatively influence industrial output growth, further revealing the under-development of productive skills and basic technical inputs for output growth in SSA.

From the estimated results, it was observed that the variable for literacy rate influenced output growth with the expectation that the ability to communicate effectively would improve general industrial output growth. While variables for school enrolment rate and average year of schooling negatively and significantly affected industrial output growth. The negative implications might be caused by a poor education system and poor opportunity cost of schooling (i.e., ineffective alternation between schooling ages and working ages). That is, the education system in SSA does not provide better alternatives for human capital skill acquisition while at school and working across different age groups. Also, poor curriculum design and lack of intellectual and political will might be responsible for school enrolment's negative and significant effect on industrial output growth in SSA. Therefore, necessary attention is needed to address the region's slow industrial output growth. The government needs to make more concerted efforts toward tackling negative returns from school enrolment rate by reconfiguring the entire education system in the region, especially across the SSA, by allowing intellectualism to thrive rather than politics, as this would extensively address the current challenges of brain drain. Based on the diverse effects of factor determinants, across and combined sub-regional policy support should be drafted to address low industrial output growth.

Also, determining factors such as information technology and access to transportation contradicted the expected economic intuitions. The indicators disclosed a negative and significant influence on industrial output growth in SSA. The implication is that SSA was characterized by poor technical progress and infrastructural spread to propel industrial sector growth. Hence, there is a need for more concerted efforts from the authorities in SSA to provide an environment that enables industrial output to thrive. Meanwhile, data such as access to energy, gross capital formation, and foreign direct investment were positive and significant but had a marginal influence on industrial output growth in SSA. More efforts are needed to improve energy sources and ease of doing business to drive domestic investment via capital formation and foreign direct investment.

However, although this study tries to fill some gaps in the literature, there is still a limitation in data accessibility that prevented the inclusion of some SSA countries in our study. Therefore, it is pertinent for future researchers to be aware of this current challenge.

4.8 DISCUSSION, CONCLUSION AND CONTRIBUTION OF CHAPTER FOUR

This study investigates industrial output growth factors across panel data drawn from 40 SSA countries. The study hypothesizes no significant effects of determining factors on industrial output growth. Notably, as part of the study's uniqueness, and to the best of our knowledge, no study has been conducted across SSA's sub-regions, as demonstrated in the study. However, few related studies have been conducted at the individual country level and other world regions. This study provides evidence of the key factors significantly influencing industrial output growth in SSA.

Correlation matrix and disaggregated two-step system GMM were adopted through an augmented endogenous model. The study rests on the reliability of robust and dynamic system GMM in addressing simultaneity and endogeneity problems in the empirical results. It has been established that estimates of SER AYS LPR LIR ICT ACE and ACT predicted industrial output growth differently across the sub-region. Fourteen variables were drawn from the empirical and theoretical framework to ascertain the true factors determining industrial output growth across 40 SSA countries. These variables were used to account for correlation to adequately curb possible collinearity problems. Also, the short-run robust and dynamic two-step GMM and long-run dynamic system GMM were adopted to examine individual estimates' short-run and long-run influence. Of the thirteen independent variables employed, nine significantly affect industrial output growth. For example, estimates such as SER LPR GCF FDI LIR ICT ACE ACT demonstrated both short-run and long-run significant effects on the industrial output growth as strong determinants of industrial output growth, while AYS and LogLBF exhibited only short-run dynamic impact.

Using appropriate diagnostics, the post-estimation tests disclosed that our outcomes are autocorrelation-free. The Robust Arellano-Bond Autocorrelation test and Hansen test of over-identifying restrictions were used to confirm the reliability of our findings. The two systems of GMM were suitable for the findings as they addressed possible simultaneity, measurement error, and endogeneity problems in the results. However, AWP, LER, and HOC variables were not statistically significant in the dynamic GMM models. This finding corroborates Bokana and Akinola (2017) and Keji (2021), which show broad perspectives on determining factors as predictors of general industrial output growth. Research policy implications and recommendations emanated from the study were based on the fact that some variables did not conform to the a priori expectation. Hence, the government must make more concerted efforts to reconfigure the entire education system across the sub-region. This concerted effort should be streamlined to allow intellectualism to strive by improving the quality of education with skill-oriented programmes. And desist from allocating an abysmal budget for education programmes to address SSA's current menace of brain drain. Based on the diverse effects of factor determinants, sub-regional policy support should be drafted to address low industrial output growth. This would bring out better human capital potentials and technical know-how for industrial output competitiveness due to different infrastructural options and human capital composition in the sub-region.

4.8.1 Contributions of Chapter Four

The preceding debate exemplified no consensus on the factors determining industrial output growth in sub-Saharan Africa (SSA). While many works have concentrated on issues related to developed countries, few have been conducted in the SSA region, and those that existed were mostly confined to specific countries. Certainly, this chapter has drawn varied emerging implications for the factors determining industrial output growth in the sub-Saharan Africa region. This study has provided the fundamental road map for policymakers to prioritise certain indicators of industrial output growth within the sub-region. Notably, these determining factors' short-run and long-run effects were disaggregated to draw dynamic effects on industrial output growth in SSA, which was unique in the extant literature. This study filled certain gaps by estimating both short-run and long-run dynamic effects of determining factors such as school enrollment rate, average year of schooling, labour participation rate, literacy rate, labour force, life expectancy rate, household consumption, access to energy, access to transportation, access to water resources, information technology, among other control and instrumental indicators through dynamic two-step GMM. Findings from the study were timely because massive investment across the determining factors would generally improve productive growth in SSA. Consequently, widening industrial output ranges from the current narrow industrial product range across the sub-region. Similarly, this would this would address current dares of poor value-added products in the sub-region, eventually putting the sub-region in the spotlight among its contemporaries such as South Asia, North America, and Europe regarding modern product identity (Fawehinmi, Omolade, & Keji, 2019; Abdulqadir & Asongu, 2021).

CHAPTER FIVE

THE COMPARATIVE EFFECTS OF HUMAN CAPITAL SKILL AND INFRASTRUCTURAL DEVELOPMENT ON INDUSTRIAL OUTPUT GROWTH IN SUB-SAHARAN AFRICA.

The purpose of this chapter is to address the second objective of the study, which is:

i) To analyze the comparative effects of human capital skill development and infrastructural development on industrial sector growth across the sub-regional economic blocs in SSA.

5.1 SUMMARY OF CHAPTER FIVE

Despite the sub-Saharan African (SSA) region's vast size regarding human capital and physical capital resources, the industrial output growth in SSA still needs to catch up to the other regions. This is because of low productive skills and the dilapidated spread of infrastructural techs, which have constrained rapid industrial growth. On this premise, the study fills gaps in the literature via trend analysis, sub-sample regression, Fixed-LSDV and disaggregated system-GMM techniques to ascertain the comparative effects of human capital skill and infrastructure development on industrial sector growth across the SSA's sub-regional blocs. Findings disclosed that Countries from the South African Development Community economic bloc (SADC) and Countries from the Economic Community of Central African States bloc (ECCAS) have better comparative effects on industrial growth than Countries from the East African Community economic bloc (EAC) and Countries from Economic Community of West African States economic bloc (ECOWAS). Notably, ECOWAS, having the highest labour force composition in its economic bloc, was found to have performed most poorly.

Similarly, a comparative analysis via Fixed Effect Least Square Dummy Variable (FE-LSDV), as suggested by the Hausman test, was adopted to examine sub-regional comparative effects across individual economic blocs in SSA. The LSDV outcomes from the combined model were compared with the LSDV outcomes from specific models to systematically reveal the comparative effects of human capital skill and infrastructure on industrial output growth. Also, disaggregated system GMM was systematically explored as a confirmatory technique to ascertain the general effects of human capital skills and infrastructure on industrial output growth. The overall results showed significant and diverse effects from human capital skill development and infrastructural-tech development on industrial sector growth across sub-regional groups in SSA. Consequently, the study suggests that countries at the sub-regional level should draft more policy support to prioritize factor inputs based on their specific comparative advantage to reduce real cost and money cost of production for rapid industrial sector growth.

5.2 INTRODUCTION

Notably, the background problems in Chapter One showed the extent of the wide gaps between human capital skills indicators, infrastructure indicators, and industrial output growth indicators in SSA. For example, recent data from world development indicators suggested that a rise in some indicators for human capital skills and infrastructure has been unable to cause any rise in industrial output, as against the extant economic and theoretical intuitions. The endogenous theorist in the neoclassical school of thought posited that output growth is caused by the accumulated comparative effects of both human and physical capital within a system of production (Aghion et al., 1998; Zhang, 2018; Abdulqadir & Asongu, 2021). The origin of endogenous theory predicted that comparative effects from human capital skills alongside infrastructural tech are needed to propel productive growth. Hence, a nation’s status of output growth is measured by the extent of the well-skilled and standard structure of both human capital and physical capital, such as infrastructure at her disposal (Du, Zhang & Han, 2022; Lin, 2017; Komla, 2018; Jorgenson & Fraumeni, 1992). The recent massive loss of highly skilled labour with viable, productive skills affects industrial output via brain drain across the sub-regions, and it has drawn more attention, forming part of the justification for the study. For example, Nigeria has lost over twenty thousand skilled labourers across critical sectors, such as the manufacturing and education sectors, among others, in recent years. Zimbabwe was the latest on the brain drain radar among many other sub-Saharan countries. It was reported that the Zimbabwean government intercepted over five hundred UK-bound medical labourers and other skilled workers on their way to the United Kingdom to reduce the downward movement of productive growth.

Remarkably, most of the small open economies across the sub-Saharan Africa region lack the significant efforts required to identify the gaps in human capital skills transformation and infrastructural investments for rapid output growth (Fedderke & Bogetić, 2006; Raheem et al., 2008; Abdulazeez & Naim, 2018; Ekwonwune Anyiam & Osuagwu, 2018; Akinola & Mbonigaba, 2019; Keji, 2021; Du et al., 2022). Abdulazeez and Naim (2018) further argued that huge infrastructural deficiencies and over-reliance on traditional means of sustaining human-physical capital have continued to prevent productive growth in SSA. Hence, the persistent increase in demand for infrastructure networks towards actualizing general output growth has continuously constrained industrial sector expansion in the sub-region. It is worth noting that human capital potential rolls alongside physical capital regarding infrastructure during the production process. These are vital inputs for industrial advancement in short- and long-run growth paths (Rebelo, 1991 & Mankiw, 1995). However, underinvestment in both human capital and infrastructural facilities has brought about slow output growth in the sub-Saharan region, increasing the cost of production and reducing value addition, particularly to productive output, thereby reducing general growth. Investment in infrastructure such as aviation, housing, electricity, ICT, railway, and road networks, among others, was poor in most SSA countries (Fedderke & Bogetić, 2006; Alani, 2018). Consequently, Figure 1, as elaborated in Chapter One, explains the likely background problems militating against productive output in SSA using the schematic concept to link apriori expectation between independent variables and dependent variables employed in the study. It was displayed schematically in Figure 1.2 to explain the impact of skills and infrastructural tech on industrial sector growth across the sub-regional economic blocs in SSA.

Based on the observations in Figure 1.2 on page 5, the recent International Labour Organisation and World Bank databases revealed the level of disconnection between the trends for industrial output, human capital skill, and infrastructure, which contradict the extant economic theory. HCD denotes an indicator for human capital skill development, IFD represents infrastructural development, and IDO denotes industrial output growth (World Bank national accounts data, and OECD National Accounts data files; World Bank Global Electrification database & UNESCO Institute for Statistics). Theory suggests that an increase in human capital potential alongside an increase in infrastructure input leads to increased output growth (Lucas, 1988; Romer & Weil, 1992).

Poor human capital skill development and infrastructure development might be responsible for the vast disconnection in Figure 1.2, resulting in low industrial output growth in SSA (Keji, 2021; Akinlo, 2022). Again, low human capital skills and a lack of necessary infrastructural tools might impede value addition to industrial goods during production, making it difficult for the region to compete globally along the supply chain. In that regard, endogenous human capital skills and infrastructural tech must be developed for higher productive growth in SSA. However, as we observed in Figure 5.1, the marginal rise in human capital and physical capital indicators in recent times was characterized by slow output growth, as shown on the trend graph, where the output return continues to nosedive across the sub-region. This further supports the earlier debates that the current state of industrial sector growth in the sub-Saharan African region contradicts expected economic intuitions due to its inability to move along with human capital skill and infrastructure development.

Notably, human capital and infrastructure comparative effects through innovating skills and modern infrastructure technology in SSA still need to improve regarding productive skill, innovations, and creativity compared to other regions such as Europe, America, and Asia. Therefore, industrial sector growth is low in sub-Saharan Africa based on the wide gap trends in Figure 1.2, which draws much to be investigated. In some quarters, few available human-physical capitals found in the region might be responsible for the recent slight increase on the graph in Figure 1.2, which has failed to translate to higher output growth (Best School News, 2022; Spy Nigeria, 2022). It is assumed that the few sharp brains around the sub-region are not well utilised, while the infrastructure presence in the region is either dilapidated or is of the old version that does not align with modern production techniques for industrial output growth. Notably, few well-skilled workforces were made vulnerable to poor work incentives, and few available infrastructures were dilapidated and less effective for product competitiveness with the advanced countries. Moreover, this has destabilised potential advancement that would have promoted industrial output growth within the sub-region blocs. Hence, it is pertinent to investigate how the highlighted background problems have impeded higher output growth across EAC ECCAS ECOWAS and SADC in SSA.

Hereafter, this study shall explore and compare all the two major strata of human and physical capital investments for productive growth regarding knowledge and infrastructural-tech effects among sub-regional economic communities in SSA. This was based on addressing the lack of knowledge on what to prioritize between human capital skill development and infrastructure-tech development by the individual sub-regional economic bloc, as they compromise industrial sector growth. This study is pertinent during this period of global challenges, as findings assist countries and sub-regions towards improving productive output with the least production costs. The remaining sections include a literature review, theoretical framework, empirical review, research methods, findings, conclusion, and recommendation.

5.3 THE TREND ANALYSIS

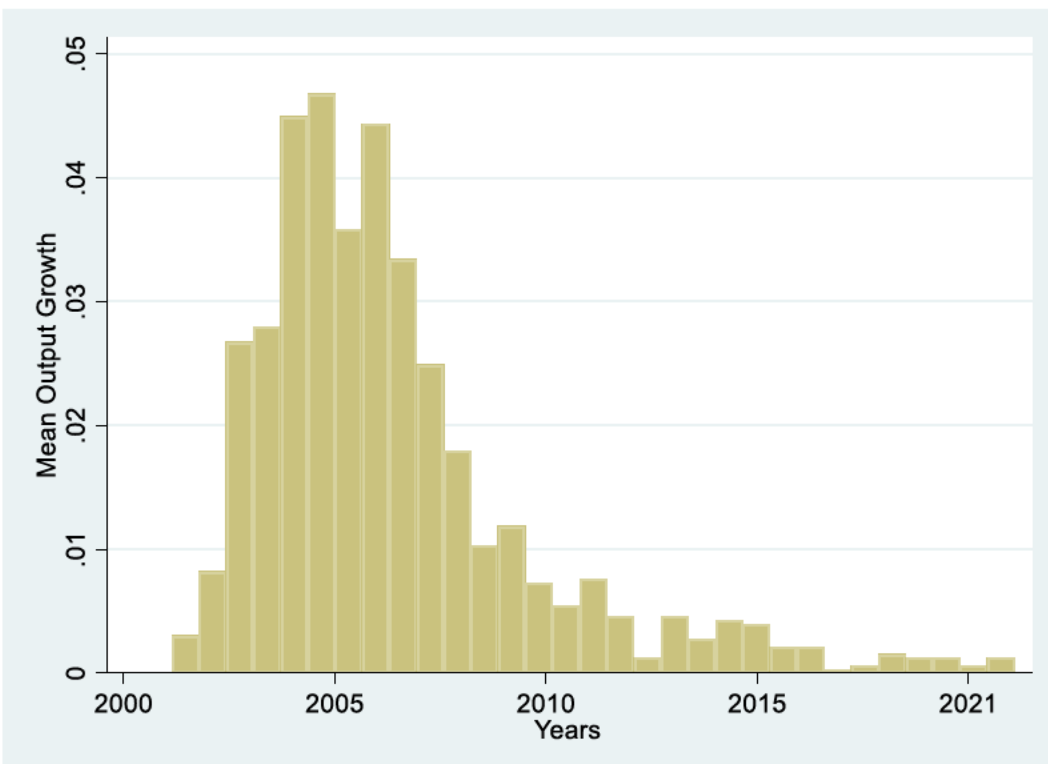


Figure 5.2: Mean Trend of Industrial Output Growth in SSA

Source: Authors' Computation, (2024).

It can be observed from the schematic illustration of the world index data in Figure 5.2 that the mean productive input from the histogram trend skewed rightwards with a fast movement towards zero in recent years. The curve implies that the output growth drops faster than the expected mean growth over the years. This means that overall productive growth diminishes over time; consequently, average output growth drops. Also, in Figure 5.3, data were collected across the sub-regional levels such as the East African Community economic bloc (EAC), Economic Community of Central African States economic bloc (ECASS), Economic Community of West African States' economic bloc (ECOWAS), and South African Development Community economic bloc (SADC) to ascertain the effects of skilled labour and infrastructure that caused industrial sector growth.

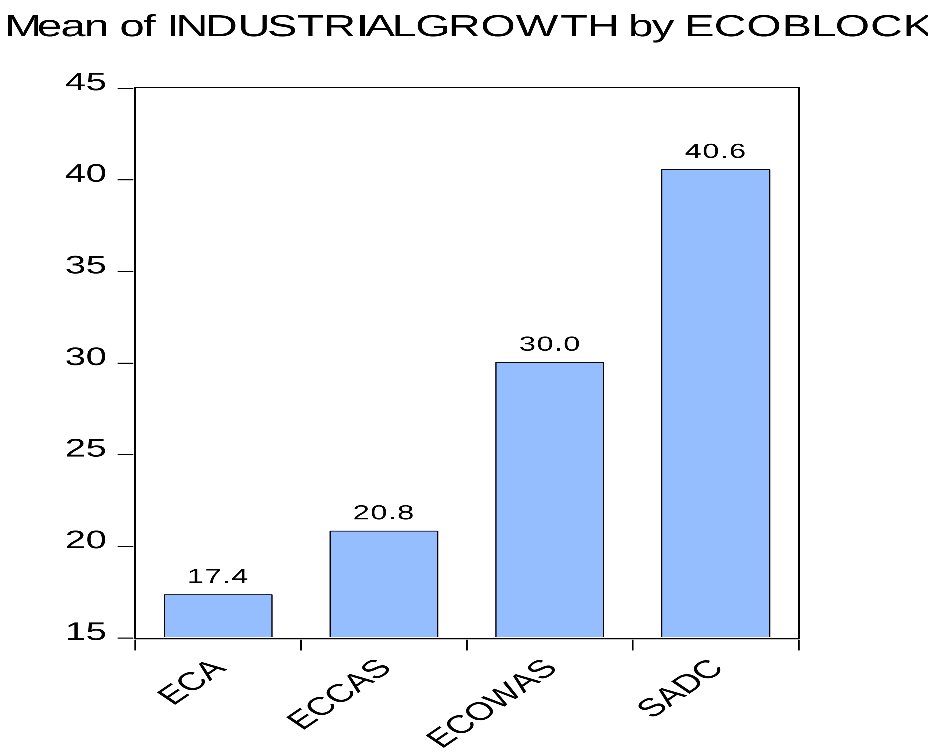


Figure 5.3: Breakdown of Sub-Saharan Regional Industrial Sector Growth.

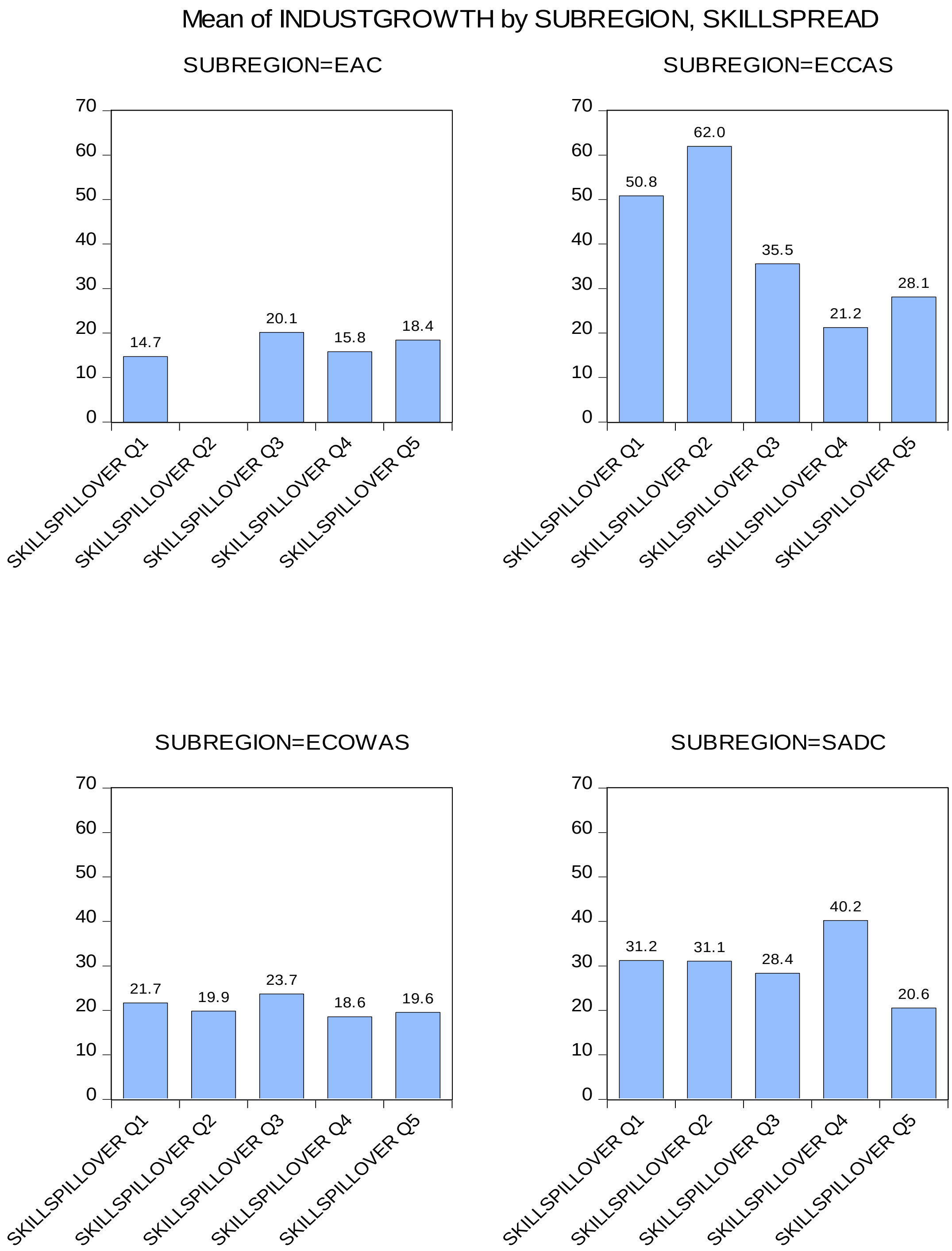
Source: Authors' Computation, (2024).

Where EAC denotes countries made up of the East African Community economic bloc, ECCAS accounts for countries made up of the Economic Community of Central African States economic bloc. ECOWAS explains the Economic Community of West African States' economic bloc. In contrast, SADC denotes information from countries comprising the South African Development Community economic bloc.

Based on the trends analysis in Figure 5.3, it is evident that industrial output growth varies among the sub-regional blocs from SSA in terms of human capital and infrastructure. Data in Figures 5.4 and 5.5 displayed individual-specific average comparative effects of the predicting factors input for industrial sector growth concerning human capital skill and infrastructural tech across sub-regional settings. Notably, SKILLSPILLOVER Q1, Q2, Q3, Q4 and Q5 explained the unit of proportion in human capital skills inputs that were employed across individual sub-regions to propel industrial output growth (Keji et al., 2024). While INFTECHSPILLOVER Q1, Q2, Q3, Q4 and Q5 denoted the unit of proportion inputs in infrastructure employed across individual sub-regional to propel industrial output growth (Keji et al., 2024). For example, under the human skill comparative effects diagrams in Figure 5.4, subregional 2, which comprises ECCAS countries, fares better regarding labour unit input than all other sub-regional blocs, followed by subregional four from SADC countries. The implication is that the unit input of labour for productive growth varies across the four sub-regional economic blocs. However, subregion one from EAC countries has the least unit of labour input with the lowest industrial output growth among other sub-regions, while ECOWAS displayed an upscale performance but fell short behind ECCAS and SADC to the third position regarding performance among all the four sub-regions. It is, moreover, shifting our attention to mean infrastructural-tech comparative effects on the industrial sector across the four sub-regional blocs in Figure 5.5. Subregion 2 from ECCAS states continues to improve, followed by subregion 4 from SADC states. In contrast, the mean infrastructural effects on the industrial sector from subregions three, comprised of EAC and ECOWAS, continued to trend below the expected average with lower infrastructure development.

The salient fact drawn from this comparative trend analysis is that the overall mean of human capital skill units-input differs and is spread across the sub-regional countries. That is, some sets of countries within the SSA region perform better than others in terms of productive growth. The bar chart revealed the average unit of output of individual sub-regions for thirty-two years, in which countries from ECCAS, SADC, ECOWAS, and EAC pulled an average output growth of about 198 units, 151.4 units, 103.5 units, and 69 units, respectively, throughout the period under review. The percentage performance regarding skill development showed that ECCAS pulled 55% average output growth throughout the period under review, followed by SADC, ECOWAS, and

EAC with 43.2%, 30%, and 5%, respectively. Even with 55, 43.2, 30, and 5% output growth rates that made up the overall performances across the SSA countries, the region still lags behind other regions of the world (World Bank, 2022).

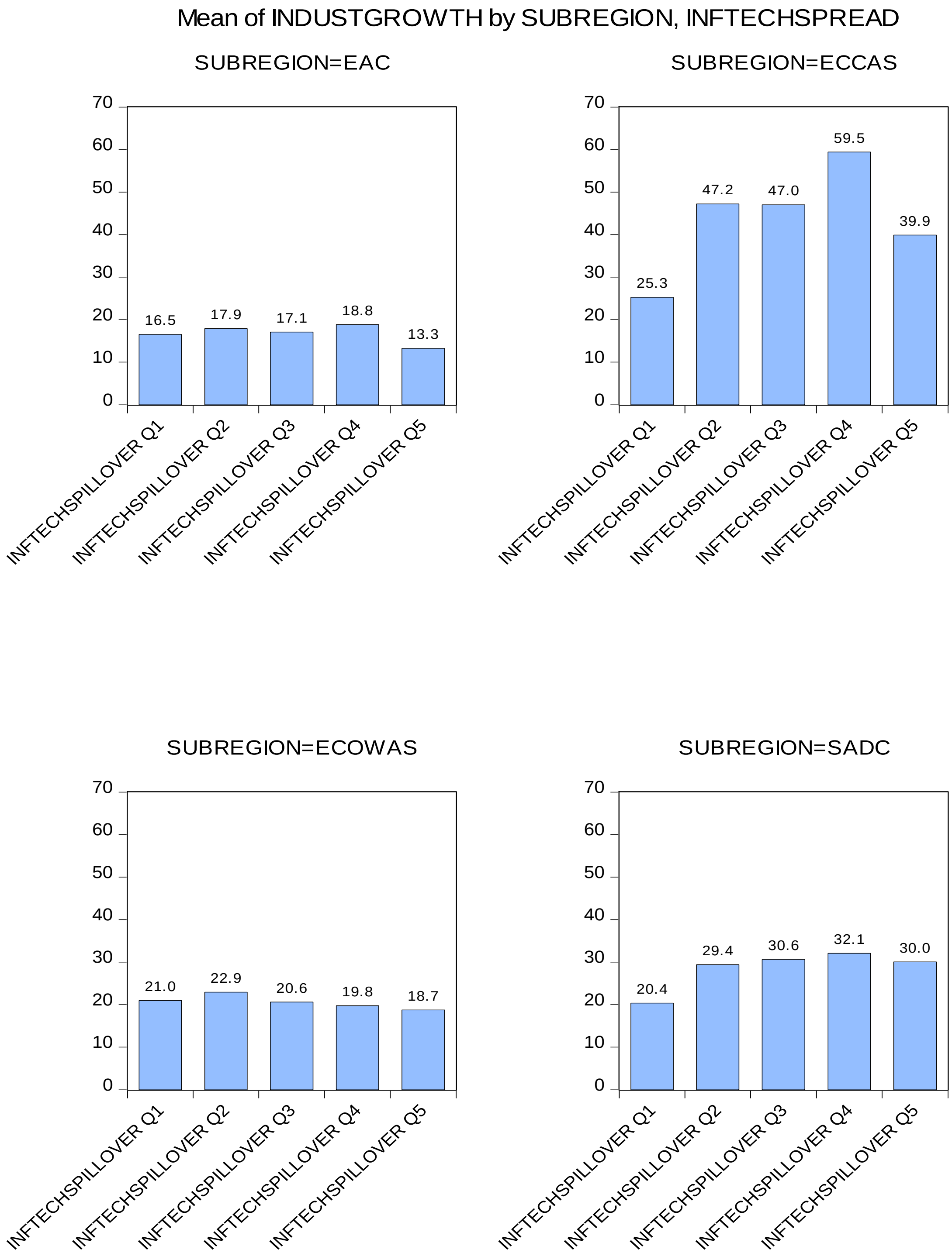


Note: SKILLSPREAD denotes mean spread effects of human capital skill development on industrial output growth across the sub-regions in SSA. This is to show individual sub-regional specific skill comparative effects across SSA.

Figure 5.4: Mean of Industrial Output Growth by Sub-regional Skill Spread

Source: Authors' Computation, (2024).

Based on the salient facts revealed in Figure 5.5 below, the comparative effects of infrastructure on industrial sector growth within the sub-region are different from the earlier figures obtained from human capital skills effects on output growth. For instance, ECCAS, SADC, ECOWAS, and EAC pulled an average output growth of about 219 units, 143 units, 103 units, and 84 units, respectively, throughout the period under review. Comparing the key factors' effects, it is observed that determinants of infrastructural tech recorded overall higher effects on industrial output growth than determinants of human capital skill. For example, ECCAS and SADC pulled 219 and 143 units of output under the influence of infrastructural development, as opposed to 198 and 151.4, which were influenced by human capital skills. The implication is that infrastructural tech has higher comparative effects on industrial sector growth across SSA countries' sub-regions than the effects of human capital skills. Based on the inferences from the trend analysis, it is obvious to advise the industrialists that investment in infrastructure tech would yield higher industrial output growth than investment in human capital, particularly during this period of financial belt-tightening facing most of those countries in SSA. It is also necessary for these countries to efficiently allocate a few available resources by prioritizing factor input that can expedite industrial growth in their respective country. We shall subject the indicators to further empirical tests in the next section to establish our salient facts further.



Note: INFTECHSPREAD denotes spread effects of infrastructural development on industrial output growth across the sub-regions in SSA. This is to show individual sub-regional specific infrastructural comparative effects across SSA.

Figure 5.5: Mean of Industrial Output Growth by Sub-regional Infrastructure Spread

Source: Authors' Computation, (2024).

5.4 THE METHODOLOGY FOR THE ANALYSIS

Working closely with studies by Romer (1986; 1990), Rebelo (1991), Akinola and Bokana (2017), Riaqa et al. (2020), Keji (2021) and Du et al. (2022) that have tried to adopt a related approach by establishing significant effects either at country level within SSA or outside sub-Saharan Africa but without paying much attention to establish the significant differences among the sub-regional economic blocs within the sub-Saharan Africa countries. Also, previous works could not ascertain and compare specific effects of human capital skill and infrastructure among the group of small open economies through sub-sample analysis. Therefore, on this premise, the study tries to fill the noted gap by investigating and comparing the effects of human capital skills and infrastructural-tech development on industrial output across the four sub-regional economic blocs in sub-Saharan Africa through sub-sample analysis, Fixed Effect LSDV and system-GMM approaches. Kiviet (1995) supported the idea that the effective way to correct possible dynamic panel bias is to employ the LSDV technique. Hence, outcomes from the study were free from statistical panel bias measurement errors, as the system GMM was later employed as a confirmatory technique to address the study's possible endogeneity and simultaneity problems (Keji, Akinola & Mbonigaba, 2024).

5.4.1 Model Specification for the Analysis

Having explained the model-building process in chapter three, it is important to specify the theoretical model for econometric modelling with necessary modifications for the empirical analysis to achieve our objectives. Hence, the econometric model is explicitly expressed as follows;

$$\mathbf{y} * = \boldsymbol{k}^{\boldsymbol{\alpha}} \boldsymbol{h}^{\beta} \ldots \ldots \ldots \ldots . . (5.1)$$

Where y= Amount of industrial Output; k=Quantity of physical capital; h=composition of Human Capital; labour as related to working age concerning output; level of Factor Productivity; α = Capital input elasticity in relationship to output Y; while β =Labour input elasticity in connection to output Y. Consequently, the 5.1 model would be implicitly discussed in line with the objective of the study.

$$\boldsymbol{logy} *_{\boldsymbol{i,t}} = \boldsymbol{\Phi h}_{\boldsymbol{i,t}} + \boldsymbol{\gamma log k}_{\boldsymbol{i,t}} \ldots \ldots \ldots \ldots \ldots \ldots \ldots 5.2$$

Expanding by introducing key and control variables for h and K in model 5.2 to become 5.3

Time and country i, t, are injected into model 5.3;

$$\boldsymbol{logy}*_{\boldsymbol{i,t}}= \boldsymbol{\Phi h_{i,t}} + \boldsymbol{\gamma logK_{i,t}} + \alpha_1\boldsymbol{AYS_{i,t}} + \boldsymbol{\alpha_2 HOC_{i,t}} + \alpha_3\boldsymbol{GCF_{i,t}} + \alpha_4\boldsymbol{FDI_{i,t}} \ldots \; 5.3$$

Based on the stated objective of partially logging h and introducing h and K, their direct indicators of measurements are assumed to be estimated to draw their combined or aggregated effects on y* and individual effects on y*.

So, let $\Phi log[h_{i,t}]= \boldsymbol{\Phi l}ogSER + \boldsymbol{\Phi} logLPR_{i,t} + \boldsymbol{\Phi} logLBF$ and let $\boldsymbol{\gamma} log[K_{i,t}]= \boldsymbol{\gamma} logICT_{i,t} + \boldsymbol{\gamma} logACE_{i,t} + \boldsymbol{\gamma} logACT$ for econometric modelling to become model 5.4;

$$\boldsymbol{logy}*_{\boldsymbol{i,t}}= \boldsymbol{\Phi l}ogSER_{\boldsymbol{i,t}} + \boldsymbol{\Phi} logLPR_{i,t} + \boldsymbol{\Phi} logLBF_{\boldsymbol{i,t}} + \boldsymbol{\gamma l}ogICT_{i,t} + \boldsymbol{\gamma} logACE_{i,t} + \boldsymbol{\gamma} logACT + \alpha_1 AYS_{i,t} + \alpha_2 HOC_{i,t} + \alpha_3 GCF_{i,t} + \alpha_4 FDI_{i,t} \ldots \; 5.4$$

Where the combined effects of human capital log (h) are evaluated side by side with the effects of infrastructural development (K) on industrial sector growth (log y*) in SSA, leveraging on the stated objective, comparing the effects of human capital skills h to the effects of infrastructure k, in models 5.4 is necessary. Hence, k and h are further disaggregated thus;

($h_{i,t}$) = comparative effects of human capital Skills

($k_{i,t}$) = Infrastructure's comparative effects

α and β = elasticity coefficient of industrial output concerning physical infrastructure and human capital in country i at time t.

$u_{i,t}$ = stochastic error terms in country i at time t.

To disaggregate into:

$H_{i,t}$= (SER LPR LBF LIR)

$k_{i,t}$= (FDI ICT ACE ACT GCF)

$y_{i,t}$= (IDO)

Where

$SER_{i,t}$ = School enrolment in country i at time t.

$LPR_{i,t}$ = Labour participation rate in country i at time t.

$LBF_{i,t}$= Labour force in country i at time t.

$LIR_{i,t}$ = Literacy rate in country i at time t.

$FDI_{i,t}$ = Foreign direct investment in country i at time t.

$ICT_{i,t}$ = Information technology/Access to the internet in country i at time t.

$ACE_{i,t}$ = Access to energy in country i at time t.

$ACT_{i,t}$ = Access to transportation in country i at time t.

$GCF_{i,t}$ = Gross capital formation in country i at time t.

$IDO_{i,t}$ = Industrial Output Growth in country i at time t.

ECA= Countries from the East African Community bloc in SSA.

ECCAS= Countries from the Economic Community of Central African States bloc.
ECOWAS= Countries from the Economic Community of West African States economic bloc.
SADC = Countries from the South African Development Community economic bloc.

Instrumental estimates

AWP= Access to clean water, ACR= Access to Rail routes, SYE= Share of youth not in education, employment or training, TRT=Total Trained Teachers in Primary and Secondary Schools.

Going forward, Fixed-Least Square Dummy Variable (FE-LSDV) models are now incorporated into countries' specific effects for econometric analysis thus,

$$\mathrm{y}*_{\mathrm{it}} = \sum_{j=2}^{k} \beta_j X_{ijt} + \partial \mathrm{t} + \sum_{t=1}^{n} \sigma_i d_i + \mathrm{E}_{\mathrm{it}} \qquad ---------------- (5.5)$$

Where Y=y*= Industrial Output growth (IDO), X= Explanatory variables, while ∂ and σ denotes a categorical dummy of time trend and cross-section countries. Converting model 5.4 for econometric analysis thus;

$$\boldsymbol{logIDO} *_{\boldsymbol{i,t}} = \boldsymbol{\beta}_{0_{\boldsymbol{i}}} + \boldsymbol{\Phi} \boldsymbol{l}ogSER_{\boldsymbol{i,t}} + \boldsymbol{\Phi} logLPR_{i,t} + \boldsymbol{\Phi} logLBF_{\boldsymbol{i,t}} + \boldsymbol{\gamma} \boldsymbol{l}ogICT_{i,t} + \boldsymbol{\gamma} logACE_{i,t} + \boldsymbol{\gamma} logACT + \alpha_1 AYS_{i,t} + \alpha_2 HOC_{i,t} + \alpha_3 GCF_{i,t} + \alpha_4 FDI_{i,t} + \boldsymbol{U}_{i,t} \ldots \ldots \ldots \ldots 5.6$$

Model 5.6 is further expanded to accommodate dummy variables for LSDV analysis;

$$\boldsymbol{IDO_{it}} = \boldsymbol{\beta}_{0_{\boldsymbol{i}}} + \boldsymbol{\beta}_1 \boldsymbol{D}_{1_{\boldsymbol{i}}} + \boldsymbol{\beta}_2 \boldsymbol{D}_{2_{\boldsymbol{i}}} \ldots \ldots + \boldsymbol{\beta}_{\boldsymbol{n}} \boldsymbol{D}_{\boldsymbol{ni}} + \boldsymbol{\beta}_1 \boldsymbol{logHCSD}_{\boldsymbol{1i}} + \boldsymbol{\beta}_2 \boldsymbol{logIFD}_{\boldsymbol{2i}} + \boldsymbol{u}_{\boldsymbol{i,t}} \ldots\ldots 5.7$$

Where HCSD encompasses all indicators for human capital comparative effects, IFD captures all indicators for infrastructural comparative effects across all the four sub-regional blocs in SSA. Model 5.7 was formulated to capture sub-regional differences in comparative effects as the dummy variables empirically account for those differences. Notably, the FE-LSDV was used to account for unobserved effects in the model by injecting dummy variable(s). Hence, this establishes the basis for determining the differences across the estimating variables through the differences among constant or shift parameters within the model. Also, unobserved endogeneity can be detected across different estimating series within the FE-LSDV model. The method is consistent, i.e., the covariance of the independent variables and error terms is close to zero. FE-LSDV can handle the heterogeneity effect. It curbs possible serial correlation and heteroscedasticity. Hence, this approach is pertinent to this study.

Models for Sub-sample Analysis

Comparison of different comparative effects across economic blocs through ECOWAS, ECCAS, EAC and SADC were achieved using the following empirical econometric codes:

Sub-sample analysis of HCSD & IFD if sub-region model in 5.7=="EAC", robust

Sub-sample analysis of HCSD & IFD if sub-region model in 5.7=="ECCAS", robust

Sub-sample analysis of HCSD & IFD if sub-region model in 5.7=="ECOWAS", robust

Sub-sample analysis of HCSD & IFD if sub-region model in 5.7==“SADC", robust

Notably, the above robust regression models were free from biased standard error. Therefore, spurious z-statistics was swiftly addressed.

Furthermore, it is important to specify the confirmatory effects through the two-step GMM model thus;

$$\boldsymbol{IDO_{it} = \Phi IDO_{it-1} + \beta_1 K_{it} + \gamma Z'_{it}} + \eta_{\boldsymbol{i}} + \eta_{\boldsymbol{t}} + \boldsymbol{u_{it}} \text{.........}\mathbf{5.8}$$

Where,

IDO is the dependent variable that denotes industrial sector growth, lag of IDO describes the past year's industrial output, K captures all the independent variables of human capital skill and infrastructure development (such as SER LPR LBF LIR ACE ICT ACT AWP), Z' is the vector of control factors (like GCF FDI), whereas the $\eta_{\boldsymbol{i}}$ elucidates unnoticed cross-country-specific impact while $\eta_{\boldsymbol{t}}$ **s**ignifies time trends in the individual country. i denotes several nations to be assessed, t implies the number of time series, $\boldsymbol{\Phi}$**,** $\boldsymbol{\beta_1}$**,** and $\boldsymbol{\gamma}$ coefficients for each control variable, and u explains the stochastic factors. Hence, the study adopted a dynamic model via sys-GMM to address measurement error, curb omitted variable bias, and curb endogeneity problems that are likely to arise (Arellano & Bond, 1991; Arellano & Bover, 1995; Blundell & Bond, 1998; Adeleye et al., 2017). Also, the Hansen test is employed to test the overall validity of the instruments.

5.5 JUSTIFICATION FOR THE ESTIMATING TECHNIQUES

Sub-sample analysis, panel analysis of the FE-LSDV regression model and two-step system Generalised Methods of Moments were adopted to compare significant differences of effects at the sub-regional level in SSA regarding the comparative effects of human capital skill development and infrastructural development on industrial output growth. A robust sub-sample analysis was used to compare the sub-regional bloc’s performance concerning the comparative effect of human skills and infrastructure on industrial output growth. In contrast, the FELSDV was adopted to show individual country-specific effects to account for unobserved effects in the model by injecting dummy variable(s). Therefore, it established the basis for determining the comparative effects across the estimating variables through the model's differences among constant terms or shift parameters. The FE-LSDV method is consistent, i.e., the covariance of the independent variables and error terms is close to zero. Also, FE-LSDV can handle the heterogeneity effect. It curbs possible serial correlation and heteroscedasticity. Hence, this approach is pertinent to this study.

Meanwhile, the two-step short-run and long-run system GMM was used to ascertain the general and confirmatory effects among the estimates. The GMM technique served as a confirmatory technique in the study. The motive of these techniques was to address the lack of knowledge on what to prioritize between human capital skill development and infrastructure development for industrial sector growth in SSA by narrowing down these comparative effects to regional economic blocs such as ECOWAS, EAC, ECCAS, and SADC. Also, based on the econometrics rule of thumb, the outcome from the Hausman test guided us on which model between fixed and random effects was suitable for the study. The Hausman statistic returned significance at 1%, which meant that fixed effects are a better and preferable technique for this study. Hence, Fixed Effects of Least Square Dummy Variables (FE-LSDV) were employed in the study to capture regional and country-specific effects on industrial output growth across SSA. System GMM was adopted to ascertain the overall effects of human capital and infrastructure, being the confirmatory model of analysis adopted to curb possible endogeneity, measurement error, omitted variable bias and simultaneity problems that may likely arise in the study.

Table 5.1: **Summary Statistics and Apriori Expectations for objective two**

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Apriori Expectation**
IDO	25.5374	13.3797	4.5559	84.3492	N/A
SER	0.8816	0.1523	-0.0535	1.4826	Positive effect
LPR	68.5099	11.7678	42.39	92.49	Positive effect
LBF	7163373	1.0200	94101	6.4500	Positive effect
LIR	59.2043	22.1698	0	101.473	Positive effect
GCF	1280	9.8967	29.9314	-81.7722	Positive effect
FDI	3.2808	7.7313	-26.6384	161.8237	Positive effect
ICT	2.2722	4.6449	0	37.6405	Positive effect
ACE	36.6379	24.6640	0.5339	100	Positive effect
ACT	20.7261	15.8749	0.1258	79.4936	Positive effect
EAC	0.225	0.4177	0	1	Cross positive effect
ECCAS	0.15	0.3572	0	1	Cross positive effect
ECOWAS	0.7227	0.4479	0	1	Cross positive effect
SADC	0.275	0.4467	0	1	Cross positive effect

Source: Authors' Computation, 2024; adapted from Worlbank data (2023).

It is evident that Table 5.1 explains descriptive statistics of the variables employed in the study. The results revealed how indicators for human capital skill and infrastructure cluster around the mean. This disclosed the level of interactions between the dependent variable and independent variables. It is glaring from the summary statistics that industrial output growth, labour participation rate, labour force, literacy rate, information technology, and access to energy move nearer to the minimum than maximum mean throughout the period under review. While indicators for gross capital formation show that foreign direct investment moves closer to the maximum than the minimum, this result implies that most of the data are relatively low within the sample period.

This corroborates the views of Fedderke and Bogetić 2006 and Abdulazeez and Naim (2018) that sub-Saharan Africa has the least level of investment in human capital skill development and infrastructural-tech development. Also, reports from the World Bank database in 2021 supported that SSA still lags behind other regions of the world in terms of industrial output growth.

Again, based on the set objective of comparing the performances of the indicators for human capital with infrastructure across the sub-regional blocs, it is evident that indicators for human capital skills move closer to the maximum than indicators for infrastructure. The sub-regional summary of the mean statistics showed that indicators obtained from ECCAS countries cluster around its mean more than the other sub-regions. This means that data drawn from these countries move around the mean more than other means from EAC, ECOWAS, and SADC within SSA. ECOWAS's mean value was quite larger than others. Based on this outcome, it is evident that sub-regional blocs possessed specific effects, which further justify the need to investigate their significant difference in output growth across the economic bloc in sub-Saharan African states.

Furthermore, in Tables 5.2 and 5.3, the correlation matrix results across the sub-region revealed a high level of weak correlation regarding comparative effects on industrial output growth. The nature of the data showed that each sub-region has particular attributes toward productive growth. The implication is that the composition of labour skill and infrastructure presence differs across the individual bloc across sub-Saharan regions; hence, their comparative effects on industrial output growth also differ. On this premise, it is pertinent to ascertain which of the determining variables of interest to prioritise for sustainable productive output growth. By extension, in this period of skyrocketing inflation across the globe, increasing output growth is the antidote to inflation. Therefore, more attention needs to be drawn to industrial output growth to curb inflationary trends, particularly among sub-regions in SSA.

Table 5.2: **Correlation Matrix of Indicators**

Variables	IDO	SER	LPR	LBF	LIR	GCF	FDI	ICT	ACE	ACT	EAC	ECCAS	ECOWAS	SADC
IDO	1													
SER	0.04	1												
LPR	-0.09	-0.12	1											
LBF	-0.04	-0.07	0.155	1										
LIR	0.236	0.495	-0.01	-0.03	1									
GCF	-0.01	-0.02	0.045	-0.01	-0.08	1								
FDI	0.069	0.061	0.033	-0.05	0.044	0.119	1							
ICT	0.003	0.329	-0.22	-0.21	0.447	-0.06	-0.01	1						
ACE	0.143	0.365	-0.47	-0.05	0.46	-0.07	-0.038	0.638	1					
ACT	-0.17	0.011	0.143	0.411	0.025	0.04	0.1564	-0.04	0.058	1				
EAC	0.08	0.06	0.153	-0.28	-0.03	0.13	0.07	-0.03	0.04	0.10	1			
ECCAS	-0.28	0.23	-0.28	-0.23	0.13	0.03	-0.07	0.04	0.21	0.30	0.64	1		
ECOWAS	0.02	0.08	-0.07	0.04	0.02	0.021	0.025	0.05	-0.05	-0.03	0.06	0.05	1	
SADC	-0.21	0.03	0.34	0.21	-0.24	0.23	-0.05	0.21	0.26	-0.16	0.91	0.06	-0.1	1

Source: Author's Computation, (2024).

The reports from individual regional coefficient correlation matrices further justify the need to ascertain the comparative effects of the regressors employed in the study on the industrial output growth across regional blocs in SSA. Generally, the crosssection of the correlation coefficients disclosed that indicators were free from possible multicollinearity as none of the coefficients was close to perfect. The outcomes from the correlation matrix rested on the results of the unit root, as the panel data are cross-sectional independent. The correlation coefficients among the series showed some level of association-ship between the dependent variable and independent variables and between the crosssection of the overall variables. Notably, there were mixed associations between the independent and dependent variables. The study noticed that IDO and ACE and IDO and LIR correlation coefficients were 0.1427 and 0.2358, respectively. Similarly, IDO and LPR and IDO and ACT coefficient values were -0.1683 and -0.0869, respectively.

Meanwhile, the cross coefficient reported between SER and ICT was 0.3286 and between LIR and ICT was 0.4472, indicating a positive but weak correlation. The implication is that our model is free from possible collinearity, particularly among the regressors. Similarly, positive relationships under this report conform to our set apriori expectations in the study. Lastly, associateships between the regressors and outcome variables have been established. Furthermore, it is pertinent to conduct a robust sub-sample analysis so as to establish whether there are significant differences among the sub-regional economies regarding industrial output growth in SSA.

Table 5.3: **Sub-regional Specific Correlation Coefficients Output**

Variables	**EAC**	**ECCAS**	**ECOWAS**	**SADC**
EAC	1.0000			
ECCAS	-0.2263	1.0000		
ECOWAS	-0.3954	-0.3083	1.0000	
SADC	0.8749	0.0549	-0.4519	1.0000

Source: Author's Computation, (2024).

Table 5.3 shows differences in productive performances concerning the comparative effects of human capital and infrastructure across the sub-regional blocs. The correlation coefficient from sub-regional specific revealed significant differences within the sub-regions. That is, the correlation coefficients among the series across the sub-regional blocs showed some level of association-ship. The crosssection of the overall variables were mixed associations, which indicate sub-regional bloc's specifics. The implication is that human capital skills and infrastructure were spread differently across the sub-region blocs in SSA. Sub-regional specifics regarding the productive strength of human capital skill and infrastructure development can be observed via the dummies correlation outcomes in Table 5.3. This is because the associationship among the dummy series was not perfect as 1.

Leveraging on the outcomes in Table 5.3, it is pertinent to estimate sub-sample analysis. This analysis encompass the individual sub-regional bloc's specifics. That is, economic bloc specifics comparative effects of human capital skills and infrastructure on industrial output growth.

Table 5.4: **Sub-Sample Analysis of Industrial Output and Comparative Differences**

Sub-regions	**EAC**	**ECCAS**	**ECOWAS**	**SADC**
	LOGIDO	LOGIDO	LOGIDO	LOGIDO
Variables	**Coefficients (t-statistics)**	**Coefficients (t-statistics)**	**Coefficients (t-statistics)**	**Coefficients (t-statistics)**
SER	-0.0621	-1.3043	.11996	-.8097
	(-0.19)	(-1.32)	(0.66)	(-3.68)***
LPR	.0125132	.01387	-.0259352	-0.0004
	(1.83)*	(1.01)	(-12.52)***	(-0.23)
LOGLBF	0.0775631	-0.2015	0.0265	0.1807
	(1.13)	(-5.10)***	(1.49)	(9.32)***
LIR	0.0062	0.0133	0.00323	0.0069
	(3.43)***	(5.80)***	(3.81)***	(4.25)***
GCF	-0.0023	0.0008	-0.0002	0.0002
	(-1.30)	(1.08)	(-0.61)	(0.21)
FDI	0.0108	-0.0034	0.0078	-0.0086
	(1.60)	(-0.68)	(2.51)**	(-1.10)
ICT	0.1027	0.2444	-0.0284	0.0045
	(3.36)***	(3.82)***	(-6.67)***	(1.24)
ACE	-0.0104	-0.0068	-0.0051	-0.0038
	(-5.44)***	(-2.04)**	(-5.67)***	(-3.65)***
ACT	-0.0007	-0.0026	-0.0015	-0.0034
	(-0.37)	(-0.96)	(-1.29)	(-2.08)**
CONS	0.9418	5.8894	4.3944	0.7261
	(1.40)	(3.06)***	(16.77)***	(2.30)**
Number of obs	201	78	315	238
F-statistics	17.89	29.27	48.67	20.65
Prob > F	0.0000	0.0000	0.0000	0.0000

Source: Author's Computation, (2024). ***Note:*** *notations of figures in parenthesis signify a level of significance at (***)1%, (**) 5%, and (*)10%, respectively. Also, coefficients and t-statistics were reported respectively..*

The sub-sample analysis results in Table 5.4 showed the resilience level among the key indicators employed in the models. Key indicators such as SER LPR LOGLBF indicating measures of human capital skill and indicators such as ICT ACE ACT as infrastructure measures were statistically significant across the four sub-regions. The implication is that each sub-region has peculiar comparative effects on industrial output growth. However, each factor input's level of comparative effects varies across the sub-regions. The empirical findings from the sub-sample analysis corroborate the outcomes of the trend analysis in terms of significant differences in comparative effects. Empirical indicators from SADC and ECCAS have better effects than EAC and ECOWAS. Generally, countries from SADC have better comparative effects of human capital skill and infrastructure on industrial output growth than other sub-regions, while indicators from EAC countries have the least comparative effects on output growth. Hence, this study estimates sub-regional specifics to address the lack of knowledge on what factor input should have been prioritised to maximize productive growth at the sub-region level in SSA. On this note, findings from the trend and robust sub-sample analysis have provided some answers to emerging questions from the study regarding policy support on what to prioritize among the two-factor inputs (i.e. human capital skills and infrastructure) at least cost of production for industrial sector growth.

Having conducted the summary statistics, the correlation matrix analysis, and sub-sample analysis. To further establish the level of relationship among the series, the study tested the appropriate relationship and the significant difference of effects between human capital, infrastructure, and industrial growth using fixed effects LSDV analysis methods.

Table 5.5: **Fixed Effects Results**

Fixed-effects (within) regression	Group: Sub-regional specifics	F(9,773) = 18.16 Prob > F **Prob > F = 0.0000**	Corr (u_i BX) = **-** 0.8302	Obs per group: Min = 6 Avg =21.6 Max = 31 Number of Obs = 820 Number of groups = 38 F test that all u_i=0: F(37, 773)=60.28		
LOGIDO	**Coefficient**	**Std. Err**	**t**	**P>t**	**[95% conf.**	**interval]**
SER	-0.9146	0.0917	-9.97	0.000	-1.0946	-0.7346
LPR	0.0071	0.0043	1.66	0.097	0.0155	0.0013
LOGLBF	0.4130	0.0744	5.55	0.000	0.2670	0.5590
LIR	0.0028	0.0008	3.71	0.000	0.0013	0.0043
GCF	0.0002	0.0003	0.72	0.472	-0.0004	0.0008
FDI	0.0022	0.0015	1.35	0.176	-0.0009	0.0022
ICT	0.0171	0.0041	4.10	0.000	0.0089	0.0253
ACE	-0.0036	0.0012	-2.99	0.003	-0.0061	-0.0013
ACT	0.0031	0.0007	4.18	0.000	0.0017	0.0047
CONS	-1.9991	1.0956	-1.82	0.068	-4.1497	0.1516

Source: Author's Computation, (2024). ***Note: Std. Err*** *denotes a standard error.*

Table 5.6: **Random Effects Results**

Random-effects GLS regression	Group: Sub-regional specifics	Wald chi2(9) = 130.03 **Prob > F = 0.0000**	Corr(u_i, X) = 0 (assumed)	Obs per group: Min = 6 Avg =21.6 Max = 31 Number of Obs = 820 Number of groups = 38		
LOGIDO	**Coefficient**	**Std. err.**	**z**	**P>z**	**[95% conf.**	**interval]**
SER	-0.7554	0.0881	-8.57	0.000	-0.9283	-0.5826
LPR	-0.0085	0.0037	-2.32	0.020	-0.0157	-0.0013
LOGLB	0.1053	0.0390	2.70	0.007	0.0287	0.1819
LIR	0.0037	0.0007	4.96	0.000	0.0022	0.0051
GCF	0.0001	0.0003	0.30	0.765	-0.0005	0.0006
FDI	0.0018	0.0016	1.13	0.260	-0.0013	0.0049
ICT	0.0193	0.0039	4.87	0.000	0.0115	0.0271
ACE	-0.0005	0.0009	-0.53	0.598	-0.0024	0.0014
ACT	0.0031	0.0008	4.20	0.000	0.0017	0.0047
CONS	2.4759	0.5555	4.46	0.000	1.3873	3.5646

Source: Author's Computation, (2024). ***Note: Std. Err*** *denotes a standard error.*

This section discusses the outcome of the fixed panel and random panel models. Based on the econometric rule of thump, it is necessary to compare the two models (fixed and random) and decide through Hausman's test which models are suitable for comparing the human capital skills and infrastructure effects on industrial output growth. Hausman's report in Table 5.7 showed a significant difference between the fixed and random effect models at a one per cent significance level. chi2(9) value at 46.55 and Prob > chi2 0.0000, which justified how the fixed effect model in the Table was better for this study than the random effect model. Adopting a fixed model in the study was premised upon the justification that it can handle the heterogeneity effects, which may influence the result of our inferences. The fixed effect model was better than the random model because it accounted for unobserved effects in the model by injecting dummy variable(s) to support the basis to determine the differences across the estimating variables through the differences among constant or shift parameters within the model. Also, unobserved endogeneity can be detected in the fixed effect model across different estimating series. Hence, the outcome from the Hausman test justifies which model is better to explain the comparative effects of human capital and infrastructure on industrial sector growth at the sub-regional level in sub-Saharan Africa.

Going by the fixed effect result, the model showed its overall significance with F (9,773) = 18.16, Prob > FProb > F = 0.0000. The interactions between the regressors and dependent variables revealed high relationships. For example, the variable for the source of human capital skill such as (ser) was negative and statistically significant at one per cent. Labour participation, which explained how skilled labour can portray the skills he/she possesses for productive growth, was positive and statistically significant at a 10 per cent level. Similarly, the labour force that explained the aggregate strength of the workforce, particularly unskilled labour, was positive and statistically significant at a one per cent level. The literacy rate employed to explain basic skills with the ability to communicate effectively showed a positive and one per cent statistical significance. At the same time, control variables such as gross capital formation and foreign direct investment that explained the basic technical level of capital to commence production and skill synergy between local and foreign expatriates via foreign direct investment for output growth were positive but not statistically significant to cause output growth across the sub-regions. All the variables, such as the ICT ACE ACT that explained infrastructure, were statistically significant in the fixed effect model. Information technology- ICT and access to transportation- ACT were positive and statistically significant at a one per cent level. While access to energy- ACT was negative and statistically significant at one per cent.

Apart from the significant difference between the fixed and random models, as disclosed through the Hausman test outcomes, some of the explanatory variables in the random effect model were biased, although statistically significant. In fact, random effect disclosed its overall significance of biased estimates, unlike the fixed effect model, which is free from biased estimates. Notwithstanding, the signs and coefficients from the two models differed, with the sign of LPR becoming negative under the random effects model as against the positive sign disclosed under the fixed effect model, which conforms to the economic intuition of a positive relationship. Also, data for access to energy dropped from the significance list of variables in the random effect model. Meanwhile, variables such as gross capital formation and foreign direct investment were insignificant in both models.

The report from the fixed effects model in Table 5.6 revealed that most of our variables conformed to our apriori expectation. Apart from variables for school enrolment and access to energy that were negatively related to industrial output growth, a unit rise in SER and ACE reduced about 0.915 and -0.004 units of industrial output growth, respectively, at a five per cent level of significant.

All other explanatory variables, such as labour participation rate, labour force, literacy rate, information technology, gross capital formation, foreign direct investment, and access to transportation, were positively related to industrial output growth. For example, a unit rise in LBF, LIR, ICT, and ACT brings about 0.413, 0.003, 0.017, and 0.003 units rise in industrial output growth, respectively, across the sub-region. Meanwhile, the random effects model revealed fewer explanatory variables that conformed to the economic intuition than the fixed effects model. The labour participation rate, school enrolment, and access to energy showed an inverse relationship with industrial output growth.

The direct and inverse relationships between the dependent and independent variables from the results further justify our previously highlighted background problems militating against industrial sector growth in SSA, as some key variables suggest otherwise to economic intuition. Hence, results of this nature constrain us from narrowing down our research and establishing the individual comparative effect of human capital skill and infrastructural tech on industrial output growth across the four sub-regions in SSA through the Fixed-Effect LSDV approach.

Table 5.7: **Hausman Test**
Ho: The difference in coefficients is not systematic. Ha: The difference in coefficients is systematic.

chi2(9)	= 46.55
Prob > chi2	= 0.0000

Source: Authors' Computation, (2024).

Table 5.7 established the relevance of the methodology for the second objective in the study. The outcomes in Table 5.7 disclosed the justification for adopting the fixed effects method over the random effects technique. This is because the Hausman probability coefficient is less than 1% level of significance. The implication is that the Fixed LSDV technique would likely reveal unbiased results in the study. While outcomes from random effect approach might possibly reveal biased outcomes in the study, as suggested by Hausman's reports (Prob > chi; 20.0000) in Table 5.7.

5.6 DISCUSSION OF FINDINGS BASED ON TREND ANALYSIS, SUB-SAMPLE ANALYSIS AND FIXED EFFECTS

In the meantime, some of the previous findings contradict the study's outcomes. Notably, the findings by Lindahl (1999), Zhang (2018), Karambakuwa, Ncwadi and Phiri (2019) were different from the discoveries in the study. For example, Zhang (2018) posited that infrastructural spread has an insignificant effect on the STI construction industry in Guangdong Province. Karambakuwa, Ncwadi and Phiri (2019) adopted FMOLS and DOLS cointegration techniques to reveal that human capital does not significantly affect output growth across the nine SSA countries. Edeme, Nchege and Dorathy (2020) reported mixed effects of infrastructure on manufacturing productive values. Whereas findings in Wei (2017), Ahmadpoury (2019), Abdulqadir and Asongu (2021) and Keji (2021) align with the empirical findings in the study. For instance, Abdulqadir and Asongu (2021) posited that infrastructural technology via access to the Internet has significant effects across the 42 SSA countries through dynamic panel data analysis. Likewise, Wei (2017) resolved that the spread of infrastructure significantly influences the Asian banking industry. Ong (2004) adopted the Needs Analysis technique to submit that knowledge as a source of innovation significantly influences firms' output performance in Singapore. Also, Keji (2021) supports the idea that human capital development determines output growth in Nigeria via ARDL and ECM techniques. Meanwhile, Muwanguzi, Olowo, Guloba, and Muvawala (2018) posited that infrastructural spread within the sub-sector of productive firms supports industrial sector growth in Uganda.

Consequently, based on the outcomes from the trend analysis, sub-sample analysis and fixed effect techniques, it has been disclosed that human capital skill and infrastructure development have joint effects on industrial sector growth in SSA, which makes this study unique. Also, each factor input portrayed diverse effects across the sub-regions in SSA. For instance, human capital skill has more significant effects on output growth in SADC than in ECOWAS; likewise, infrastructural spread in ECCAS and SADC have more significant effects compared to EAC and ECOWAS. In the meantime, the outcomes of this study are timely, and it could possibly provide policy direction for SSA countries, as posited by Muwanguzi et al. (2018) in the case of Uganda's Vision 2040.

Findings from the trend analysis in Figure 5.2 imply that the output growth dropped faster than the expected mean growth over the years. This means that overall output diminishes over time; hence, average output growth drops. While outcomes from Figure 3 reflected that EAC countries have the least unit of labour input with the lowest industrial output growth among other sub-regions. Results in Figure 4 disclosed that EAC and ECOWAS trend behind ECCAS and SADC regarding expected average spillover from human capital skills development. Likewise, findings in Figure 5.3 revealed that EAC and ECOWAS trend below the expected average comparative effects via infrastructure.

Going forward, the outcomes of the comparative effects of human capital skill development and infrastructure development are found in Table 5.8. The comparative reports were in three different levels of comparative effects across sub-regional economic blocs in sub-Saharan Africa. In the first place, it is an attempt to estimate the combined effects of human capital skill and infrastructure on industrial sector growth across the sub-regions. Secondly, estimate specific effects of human capital skills on output growth at country and sub-regional levels. Thirdly, to ascertain the specific effects of infrastructure on industrial growth at country and sub-regional levels using the FE-LSDV method. The LSDV models in Table 5.8 were adopted for the comparative analysis encompassing the sub-regional effects of improved human capital skill and infrastructure development on industrial sector growth in SSA. The coefficients on school enrolment rate, labour participation rate, literacy rate, labour force, information technology, and access to energy and transportation may comprehensively explain how much human skill and infrastructure development manifest to improve industrial output growth. The fixed-LSDV in Table 5.8 reported for combined comparative effects model found in columns 2 and 3 of the Table. While Columns 4 and 5 accounted for the specific effects model of human capital skills.

Meanwhile, columns 6 and 7 reported and explained the specific effects model of infrastructure. This tabular arrangement puts all the comparative effects into perspectives for suitable statistical comparison. Notably, fixed effects-LSDV and equality tests were used in the study because they complement each other. The results from equality statistics in Table 5.14 further justified that most explanatory variables have different comparative effects on output growth.

Table 5.8: **LSDV fixed effects: A Comparative Analysis of Sub-regional Effects**

Variables	**Joint**	**Effects**	**Human Capital**	**Skill Effects**	**Infrastructure**	**Effects**
	R-squared	= 0.7971	R-squared	= 0.7734	R-squared	= 0.7636
	Adj R-squared	= 0.7851	Adj R-squared	= 0.7651	Adj R-squared	= 0.7508
LOGIDO	Prob > F	= 0.0000	Prob > F	= 0.0000	Prob > F	= 0.0000
	F(46, 773)	= 66.03	F(45, 1232)	= 93.59	F(42, 777)	= 59.76
	No of obs	= 820	No of obs	= 820	No of obs	= 820
	Coefficient	**P-value**	**Coefficient**	**P-value**	**Coefficient**	**P-value**
SER	-0.9146	0.000	-0.5154	0.000		
LPR	-0.0071	0.097	-0.0091	0.001		
LOGLBF	0.4130	0.000	0.0791	0.000		
LIR	0.0028	0.000	0.0018	0.001		
GCF	0.0002	0.472	-0.0001	0.749	-0.0000	0.954
FDI	0.0021	0.176	0.0023	0.015	0.0014	0.396
ITC	0.0171	0.000			0.0204	0.000
ACE	-0.0037	0.003			-0.0003	0.708
ACT	0.0032	0.000			0.0021	0.008
R_id			**@Sub-Regional**	**Spillovers**		
	Joint	**Effects**	**Skill-comparative**	**Effects**	**Infra-comparative**	**Effects**
Effects across Sub-regions →	**Coefficient**	**P-value**	**Coefficient**	**P-value**	**Coefficient**	**P-value**
EAC	0.5104	0.000	0.6358	0.000	0.8214	0.000
ECCAS	1.6019	0.000	0.3961	0.000	0.4331	0.000
ECOWAS	0.7894	0.000	0.0576	0.550	0.0561	0.462
SADC **(Cons)**	-1.9893	0.085	3.0241	0.000	3.1433	0.000
C_id			**@ Country**	**Specifics**		
	Joint	**Effects**	**Skill comparative**	**Effects**	**Infra-comparative**	**Effects**
Effects across Countries →	**Coefficient**	**P-value**	**Coefficient**	**P-value**	**Coefficient**	**P-value**
Benin	-0.5887	0.000	-1.016	0.000	-1.1424	0.000
Botswana	1.0455	0.000	-0.0627	0.433	-0.2420	0.027
Bu. Faso	-0.6729	0.000	-0.6994	0.000	-0.9291	0.000

Variables	Joint	Effects	Human Capital	Skill Effects	Infrastructure	Effects
Burundi	-0.8173	0.000	-1.0306	0.000	-1.3655	0.000
Capo,Verde	0.5088	0.112	-0.6437	0.000	-1.0818	0.000
Cameroon	-0.5699	0.000	-0.5949	0.000	-.71232	0.000
Chad	-1.1631	0.000	-1.3389	0.000	-1.4073	0.000
Comoros	-0.0329	0.924	-1.4188	0.000	-1.5629	0.000
Congo, DR.	-2.2505	0.000	-0.5847	0.000	-.3724	0.000
Congo, Rep.	0.3734	0.000	0.3733	0.000	0.3733	0.000
Cote d'Ivoire	-2.1784	0.000	-0.8544	0.000	-0.7057	0.000
E. Guinea	0.3693	0.000	0.5691	0.000	0.5349	0.000
Eritrea	-0.5032	0.000	-0.5031	0.000	-0.5031	0.000
Ethiopia	-2.1764	0.000	-0.8671	0.000	-0.6725	0.000
Gabon	0.7515	0.000	0.62712	0.000	0.71705	0.000
Gambia	-0.5503	0.000	-0.5452	0.000	-0.8977	0.000
Ghana	-0.9325	0.000	-0.1327	0.115	-0.0191	0.805
Guinea	-0.5212	0.000	0.0223	0.770	0.1249	0.069
Guinea B.	-0.3235	0.001	-0.4937	0.000	-0.6724	0.000
Kenya	-1.5929	0.000	-0.5501	0.000	-0.3576	0.000
Lesotho	0.3337	0.001	0.38921	0.000	0.3103	0.000
Madagascar	-1.1701	0.000	-0.2598	0.019	-0.3181	0.000
Mali	-1.0391	0.000	-0.3353	0.000	-0.2238	0.001
Mauritania	0.0593	0.447	0.0462	0.492	0.1174	0.066
Mauritius	0.1312	0.087	-0.0505	0.403	-0.0992	0.148
Mozambiqu	-1.3816	0.000	-0.4249	0.000	-0.3319	0.000
Niger	-0.2193	0.021	-0.2005	0.004	-0.1539	0.055
Nigeria	-0.9314	0.000	-0.2169	0.030	-0.4095	0.000
Rwanda	-0.1398	0.089	-0.2033	0.001	-0.0266	0.744
Senegal	0.0989	0.568	-0.2001	0.069	-0.6746	0.000
Sierra Leone	-0.3856	0.005	-0.6988	0.000	-0.0329	0.733
South Africa	-0.6731	0.000	-0.1687	0.059	-0.7857	0.000
Sudan	-0.8492	0.000	-0.6374	0.000	-0.0354	0.676
Tanzania	-0.5398	0.000	-0.1443	0.021	-0.4676	0.676
Togo	-0.2232	0.162	-0.4609	0.000	-0.0191	0.805
Uganda	-0.3237	0.001	-0.2983	0.000	-0.2225	0.009
Constants	-1.9893	0.085	3.0241	0.000	3.1433	0.000

Source: Author's Computation, (2024).
Note: *R_id denotes Regional identity, and C_id implies country identity.*

Explanation of the LSDV results in columns 2 and 3 in Table 5.8

From the combined level of the equation in the LSDV results, school enrolment, labour force, literacy rate, information technology, access to transportation, labour participation rate and access to energy were statistically significant across all the sub-regions. Meanwhile, gross capital formation and foreign direct investment coefficients were not statistically significant. Based on our apriori expectation of association-ship among the series, all variables except access to energy, school enrolment, and labour participation rate conformed to the apriori assumption. This outcome implies that some of these variables have an inverse relationship with productive growth, which contradicts the theory's suggestion. For example, a unit rise in school enrolment and labour participation rate brought about a 0.915 and 0.007 units fall in output growth, respectively. This might be connected to the poor educational curriculum and the need for up-to-date skills to match the modern production system across the sub-region. As demand for improved productive skills is growing, e.g. artificial intelligence, data science, machine and deep learning, programming, market automation, and blockchain tech, among others, are currently sought after to boost industrial output growth (Spy Nigeria, 2022). It is quite challenging that SSA is off the track regarding modern technology and high-tech skills to support the new dynamic for productive growth.

Meanwhile, results from sub-regional dummies in the joint estimating equation showed the degree of elasticity differences across the sub-region. That is, different comparative effects within the SSA region were significant. The difference in degree of comparative effects across all the regions is -1.989253, and with a negative coefficient estimate, it was evident that productive growth is constrained in the sub-regions by one form of perennial problem or the other.

Explanation of the LSDV results in columns 4 and 5 in Table 5.8

The FE-LSDV outcomes reported in columns 4 and 5 captured specific human capital skill models, all things being equal, ceteris paribus. This is to ascertain an independent comparative of human capital skills on industrial output growth while infrastructure measures were held constant, all things being equal. Emerging outcomes disclosed that human capital skills significantly predicted industrial output growth across the sub-regional blocs in SSA. For example, measures for school enrolment-SER and labour participation rate were negative and statistically significant at 1% levels. A unit rise in SER and LPR caused about 0.5154 and 0.0091 fall in industrial output growth in SSA. This was connected to poor human skills development in the region.

Meanwhile, measures for labour force-LOGLBF, literacy rate-LIR, and foreign direct investment-FDI were positive and statistically significant at 1% and 5% levels, respectively. A per cent rise in

LOGLBF brought about a 7.911 per cent rise in industrial output growth. The implication is that an increase in the labour force in SSA propelled increased industrial output. Also, a unit rise in LIR and FDI brought about a 0.0019 and 0.0023 rise in industrial output growth in SSA. Evidence from the sub-regional blocs via the dummies variables revealed significant differences in the degree of comparative effects across ECA ECASS, ECOWAS and SADC. The degree of differences in comparative effects stood at 3.024057, much higher regarding specific skills under the human capital model than the combined model, where the two key variables-human capital and infrastructure, were jointly estimated.

Explanation of the LSDV results in columns 6 and 7 in Table 5.8

The specific infrastructure model outcomes were reported in columns 6 and 7 of Table 5.8. The motive was to ascertain infrastructural tech's specific effect on industrial output growth, all things being equal. Going forward, this would pave the way for comparative analysis of different effects. The overall outcomes disclosed that infrastructure significantly predicts industrial output growth in SSA. For example, indicators for infrastructure such as information technology (ICT) and access to transportation (ACT) were reported to be statistically significant at one per cent. A unit increase in ICT and ACT brought about 0.0204 and 0.0021 units in industrial output growth. Also, under the sub-regional evidence, the results showed significant differences in the comparative effects of infrastructure on industrial output growth. SADC reported a 3.14327 level of differences caused by infrastructure on the industrial output being the reference point. This disclosed the high level of one per cent significance differences among the sub-regional economic blocs. At the country specifics, the constant terms reported disclosed some levels of significance differences within the model. As the reference dummy, Zimbabwe was reportedly significant across the three models. As suggested by econometric intuition, a proxy of Zimbabwe by constant terms was to avoid the dummy trap.

Additionally, from the result in Table 5.8, it was shown that school enrolment rate (SER), literacy rate (LIR), gross capital formation GCF), literacy rate (LIR), information technology (ICT) and access to energy (ACE) were statistically significant across the economic bloc. Among the five significant variables, only SER, ACT, and ICT are inversely related to IDO, literacy gross capital formation (GCF), and literacy rate (LIR), which directly impact IDO. It is therefore implied that, for a unit rise in (GCF) and (LIR), IDO would rise by a unit increase of 0.54 and 0.22, respectively, on average, all things being equal, while a unit increase in (SER) and (ICT), decrease IDO by 89. 0 and 2.0, respectively in SSA.

A further investigation has confirmed the LSDV outcomes through short-run and long-run system dynamic GMM models. Notably, the weakness of the endogeneity problem in LSDV has been overcome via the GMM analysis based on the evidence provided through robust system GMM results. The evidence of interactive effects subsists within the dynamic system GMM model, which is suitable for the analysis. Human capital skills and infrastructure development effects change over time. Therefore, assessing these dynamic effects via the dynamic system GMM model that accounts for the time path is pertinent.

Table 5.9: **Short-Run Dynamic, Two-Step System GMM as Confirmatory Techniques (Robust)**

Number of instrument = 37 Group variable: c-id	Number of observation = 760	Wald chi2(15) = **741.80** Prob> chi = **0.0000**	Obs per group: min= 5 Avg. = 20.00 max = 25	Time variable = Years Number of groups = 38
Variables	**Co-efficient**	**Corr. Standard Error**	**Z-statistics**	**Prob. Value**
LagIDO	0.4063	0.1750	2.32	0.020
SER	-89.7555	31.7777	-2.82	0.005
LPR	-0.1541	1.2223	-0.13	0.900
LOGLBF	-3.5573	5.9098	-0.60	0.547
LIR	0.5412	0.2879	1.88	0.060
GCF	0.2264	0.0948	2.39	0.017
FDI	0.6429	0.7531	0.85	0.393
ICT	-2.0372	0.9334	-2.18	0.029
ACE	0.2664	0.1624	1.67	0.090
ACT	-0.2057	0.3493	-0.59	0.556
Cons.	125.6012	90.3389	1.39	0.164

Source: *Author's Computation, (2024).*

In Table 5.9, the robust option of standard error was adopted in the study to control the downward bias of the standard error coefficients to curb the superfluous z-value. Hence, the short-run GMM results confirmed the comparative effects of human capital skills and infrastructure on industrial output growth across sub-regional blocs. The study adopted the two-system GMM as a confirmatory technique from the FE-LSDV. Remarkably, the effects of collaboration among the estimates were revealed. For example, SER LIR GCF ICT and ACE, as indicators for human capital skills and infrastructure, further disclosed their significant effects on industrial output growth in SSA. Hence, findings of the Syst-GMM showed improved confirmatory results from the F-LSDV model in Table 5.9 as it disclosed dynamic effects of the key variables, having control endogeneity and simultaneity problems that might likely arise. The post-estimation results were reported thus.

Table 5.10: **Robust Arellano-Bond Autocorrelation Test**

Ho: no autocorrelation	
Arellano and Bond test for AR(1) z = -2.23	Pr > z = 0.025
Arellano and Bond test for AR(2) z = 1.10	Pr > z = 0.273

Source: Authors Computation, (2024).

Table 5.11: **Hansen test of over-identifying restrictions**

Ho: Over-identifying restrictions are valid	
chi2(27)	= 26.32
Prob > chi2	= 0.501

Source: Authors Computation (2024).

The results of the Robust Arellano-Bond autocorrelation tests for higher-order and lower-order autocorrelations and the Hansen/Sargan test of over-identifying restrictions were reported in Tables 5.10 and 5.11, respectively. To determine the autocorrelation levels, Arellano–Bond opined that an autocorrelation test should be done on the levels residuals as against the differenced levels, which can only be achieved via system GMM (Roodman, 2009). The autocorrelation results disclosed that our model is free from possible incidences of autocorrelation, as autocorrelation in the lower order (bond) was self-corrected in the higher order (bond) of the autocorrelation model. Also, the Hansen/Sargan test statistic conventional rule of thumb posits that the null hypothesis of "the instruments as a group which are exogenous." Hence, the Hansen p-value is less than one, which indicates better Hansen statistics. Therefore, the Hansen coefficient in Table 5.11 rejected the null hypothesis that group instruments were strictly not exogenous, meaning over-identifying restrictions were invalid. Hence, the GMM instruments employed in the study were free from adverse effects on the results. Consequently, our models in the study were reliable, consistent, and valid in identifying the comparative effects of human capital and infrastructure on industrial sector growth across the economic blocs in SSA. Having explored the effects of the independent variables that were significant in the short-run GMMM model, it is pertinent to ascertain their long-term dynamic effects via long-run system GMM as part of the novels in the study.

Table 5.12: **Results Showing the Empirical Implications of the Robust System-GMM Model**

Indicators (Variables)	Sys-GMM Coefficient	Corrected Std. Error (Corr. Std Err.)	(XSys-GMM Coefficient)X(Corrected Std. Err.) => Sys-GMM*Corr. Std Err.	Empirical Impact (EI)
IDO	0.4063	0.1750	0.0711	
SER	-89.7555	31.7777	-23522236.70	-57889490.6
LIR	0.5412	0.2879	0.1559	0.3836
GCF	0.2264	0.0948	0.0215	0.0528
ICT	-2.0373	0.9333	-1.9015	-4.6797
ACE	0.2664	0.1624	0.0433	0.1065

Source: *Author's Computation, (2024).*

$$EI = \frac{\mathrm{XSys - GMM * C.\,Std\ Err.}}{\mathrm{YIDO\ Corr.\,Std\ Err.}}$$

Where, Sys-GMM*Corr. Std Error denoted multiples of the individual explanatory variable coefficient and their respective corrected standard errors, while YIDO Corr. Std. Error explained the product of the explained vary and its corrected Standard Error—EI coefficient of the empirical impact of the confirmatory system-GMM outcomes.

5.6.1 The Empirical Impact of the Robust System Gmm Result

Table 5.12 addresses the empirical impact of the confirmatory system GMM results. This estimation corroborated the argument of Kwenda and Holden (2013), which drew necessary inferences between the outcome variable corrected the standard error and their explanatory variables. The findings showed that any adjustment in standard error in SER would lead to a 57889490.6 units decrease in industrial output growth. Meanwhile, a unit change in standard error LIR GCF ACE would lead to a 0.38356, 0.05281, and 0.10646 units increase in industrial output growth, respectively. Meanwhile, a slight change in standard error in ICT would lead to a decrease of 4.67971 units in industrial output growth. It can observed that sources of human capital skills development and infrastructure development, such as SER and ICT, exhibited negative implications on industrial output growth in SSA. These results showed that poor school enrollment and access to information technology disrupt industrial output growth. Even the positive implications from LIR GCF ACE indicators were not encouraging due to their marginal effects on industrial output growth.

5.6.2 Model for Long-Run Dynamic Panel-Data Estimation, Two-Step System Gmm

The empirical analysis of long-term system GMM rested on the following statistical assumptions and formulas:

$$\boldsymbol{\beta\_\eta / [1\text{-}\Phi]}$$

Where β_η denotes the significant coefficient of the short-run system GMM estimate, Φ explains the short-run lag-dependent estimate coefficient of the system GMM. This is another contribution of the study to the empirical literature, as the study considered the time path of comparative and dynamic effects from human capital skills and infrastructure tech, which is rare among mainstream economic studies. Findings from Table 5.12 showed that all indicators of infrastructure tech and human capital skills except access to energy exhibited long-run dynamic effects on industrial sector growth in SSA. For example, school enrolment, gross capital formation literacy rate and information techs were statistically significant in the long run. Consequently, foreign collaborations would positively influence industrial output growth via foreign direct investment in the long run across the sub-region. The implication is that investments in education and information techs have long-run dynamic effects on industrial output.

Consequently, assuming the sub-regions try to prioritize factor input by concentrating more on either factor input. That is, either human capital skill development or infrastructure tech development. To answer this case scenario, models for factor-specific human capital skills and infrastructural tech were reported differently in columns 4 and 5 and 6 and 7. The models were consistent with the number of significant explanatory variables under the joint model but better off regarding country-specific effects within the sub-region. SER, LPR, LOGLBF, LIR, ICT, and ACT coefficient estimates are all statistically significant in factor-specific models. The significant differences regarding comparative effects were positive in the factor-specific models as against negative in the combined model.

Table 5.13: **Long-Run Dynamic Panel-Data Estimation, Two-Step System GMM (Specific Effects)**

Statistics	Coefficient.	Std. Err.	Z statistics	P>|z|	95% Conf. Interval
SER	-151.1877	51.4712	-2.94	0.003	-252.0694 -50.3059
LIR	0.9117	0.4992	1.83	0.068	-2.4259 0.1007
GCF	0.3814	0.1803	2.11	0.034	0.0279581 0.7349
ICT	-3.4317	1.5161	-2.26	0.024	-6.4033 -0.4600
ACE	0.4487	0.2889	1.55	0.120	-0.1176 1.0150

Source: *Author's Computation (2024).*

5.6.3 Discussion of the Long-Run System-Gmm

The motive of the system GMM model in Table 5.9 was to disclose the consistency of our findings from the FE-LSDV. That is, by revealing the consistency of the regressors' comparative effects from those significant indicators both in the short-run and the long-run models (Arellano & Bond, 1991; Arellano & Bover, 1995; Blundell & Bond, 1998; Adeleye et al., 2017; Roodman, 2009). Notably, the key variables, such as SER LIR GCF ICT and ACE, were statistically significant under the short-run dynamic model and were the variables of interest in this section. Consequently, the outcomes under the long-run system GMM were disclosed as follows. A unit rise in the SER-school enrollment rate brought about a 151.2 unit fall in industrial output at a 1% significant level in the long run. This contradicts apriori expectation, which implies a proactive policy that can reconfigure the education system in SSA. Also, a unit increase in LIR-literacy rate brings about a 0.912 increase in industrial output growth in the long run, which supports the apriori expectation of positive association-ship between the independent estimate and dependent variable. The implication is that an increased ability to communicate effectively contributes immensely to long-term productive growth across the SSA. Meanwhile, infrastructure measures such as ICT-

Information technology disclosed that a unit rise in info-tech brought about a 3.432 unit fall in industrial output at a five per cent significant level in the long run across the SSA. This is evidence of poor infrastructural spread across the region because this contradicts apriori expectation, which implies proactive policy for massive reconfiguration of the current state of infrastructural spread regarding industrial output growth in SSA.

In contrast, data for ACE-Access to energy revealed an insignificant effect on industrial output growth in the long run, as against the significance reported under the short-run-GMM model. By implication, the influence of access to energy for industrial sector growth in SSA was short-lived, resulting in slow industrial output growth. Hence, concerted efforts are needed to improve infrastructural inputs for massive industrial output growth across SSA.

Meanwhile, one of the control factors for investment in human capital skill and infrastructure development proved significance in the long run. Data for gross capital formation disclosed a five per cent level of significant in both short-run and long-run. That is, a unit rise in GCF-gross capital formation as a major source of local investment across different countries brought about a 0.318 units increase in industrial output growth. This implies prioritizing domestic investment within the sub-region based on its resilience over foreign direct investment due to its significant control of industrial sector growth in SSA.

5.6.4 The Equality Test for Differences in Comparative Effects within the Models

Furthermore, a comparative analysis of the effects of different countries was disclosed along with each of the estimating equations, and most of the countries revealed significant comparative effects on industrial sector growth. Again, we perform an equality test to confirm and establish our results from FE-LSDV. This is to ascertain whether estimated variables cause industrial sector growth differently or not. The outcome in Table 5.12 disclosed the details of our findings. From the results, all series affect industrial sector growth differently except LPR and ACE, which are jointly not different from zero. By the rule of the majority, it can be established that comparative effects from the key independent indicators impacted the industrial output growth in SSA differently. Therefore, authorities in SSA must prioritise which critical indicators can have a higher impact on industrial output growth.

Table 5.14: **Equality Test for Comparative Effects**
Ho: Individual explanatory variables equally affect the dependent variable.
Ha: Individual explanatory variables affect the dependent variable differently.

Variable	Test of Equal Effects Between Determinants	F- Statistics	P-value (Prob > F)
Log	Ho:		
SER and ICT	SER = ICT	F(1, 773) = 103.23	0.0000
SER and ACE	SER = ACE	F(1, 773) = 98.75	0.0000
SER and ACT	SER = ACT	F(1, 773) = 99.97	0.0000
LPR and ICT	LPR = ICT	F(1, 773) = 17.92	0.0000
LPR and ACE	LPR = ACE	F(1, 773) = 0.65	0.4205
LPR and ACT	LPR = ACT	F(1, 773) = 5.84	0.0159
LOGLBF and ICT	LOGLBF = ICT	F(1, 773) = 27.26	0.0000
LOGLBF and ACE	LOGLBF = ACE	F(1, 773) = 30.62	0.0000
LOGLBF and ACT	LOGLBF = ACT	F(1, 773) = 30.32	0.0000

Source: Author's Computation, (2024).

5.7 CONCLUSION, CONTRIBUTIONS AND RECOMMENDATION

This research attempts to estimate the comparative effects of improved human capital skills and infrastructure on industrial output growth within the sub-regional blocs in SSA using trend analysis, robust sub-sample analysis and FE-LSDV techniques. Findings from this study established that SADC and ECCAS continue to do better in infrastructure, as reflected in both trend and LSDV analysis with marginal comparative effects on industrial output growth. The minimal effects could be attributed to SSA's low composition of highly skilled human capital and modern infrastructure technology, leading to slow industrial sector growth. Economic tuitions on the relationship between human capital skill, infrastructure, and industrial output growth appear to have been established in the cause of our findings. Consequently, the study provided evidence that our objectives in this study have been achieved. Lucas (1988) opined that consistently utilising human and physical capital improves output growth.

In contrast, Rebelo (1991) posited that human capital improves output growth, mainly when it is at the breakeven with technology. Mankiw, Romer, and Weil (1992) developed the augmented endogenous assumption that improving human capital skills quickly adjusts to emerging technical progress for output growth. Our empirical findings reflect sub-regional performance regarding infrastructure and labour skill composition on output growth. In the model for human capital effects on industrial growth, the ECOWAS region has the largest labour (including Nigeria) size without a corresponding increase in human capital spillover effects, hence low industrial growth. Meanwhile, SADC with a smaller labour size was significant in the result table.

5.7.1 Contributions of Chapter Five

The preceding argument exemplified a scanty study on the comparative effects of human capital skills and infrastructure on industrial output growth across sub-regional economic blocs in SSA; few that have been identified cannot be generalised. Similarly, the few selected studies on individual countries and other regions across the globe showed diverse views on this issue, and the indicators that needed to be prioritised between human capital skills and infrastructure for industrial output varied from country to country. To the researcher's knowledge, no study has focused on the comparative effects of human capital skills and infrastructure on industrial output growth across sub-regional economic blocs in SSA, making this study unique.

Consequently, this study contributes to the literature by narrowing down the extent to which factor inputs such as knowledge and technical progress spread through human capital skill and infrastructure development on industrial sector growth among the small open economic blocs in SSA. Also, the study tries to compare the country's performance with their sub-regional bloc performance regarding industrial output growth. This is to guide the industrialists and the key players in the industrial sectors on what to prioritize between the two-factor inputs (human capital or infrastructure) for rapid industrial sector growth based on their sub-regional bloc-specific needs and comparative advantage. To the best of our knowledge, the previous studies have yet to work in this direction by putting all the sub-regional economic blocs (EAC ECCAS, ECOWAS and SADC) into perspective using sub-sample analysis, FE-LSDV and confirmatory system GMM. However, they addressed the sub-region as a whole using different estimating techniques. Therefore, this fills the gap in the existing empirical literature.

Furthermore, these findings are based on recent global developments focusing on continental infrastructural development and are part of sustainable development goals towards building resilient infrastructure across different regions. Findings from this study are timely towards accomplishing some Sustainable Development Goals (SDGs), particularly the ninth SDG towards building resilient infrastructure, promoting inclusiveness, sustainable industrialisation and fostering innovation, among others, promising on the United Nations 2030 Agenda for Sustainable Development as pronounced in 2015 (African Development Bank, 2018; 2019).

5.7.2 Recommendations

Given this, the study deduced and recommended that the ECOWAS sub-region infrastructural set-up was poor but better off regarding human capital size without the sustainable skill to spur industrial sector growth. Hence, ECOWAS countries should strive to improve human capital skills through rapid policy support and investment in the education system and general well-being. ECCAS and SADC are fair regarding infrastructure but lack high-tech labour skills to match the high-tech labour demand, so the sub-regional blocs need to redesign their education curriculum and configure it to suit the current market labour demand; EAC is lagging behind other sub-regions and must invest in both factor inputs (Human capital skills and infrastructure), but it can quickly adjust through rapid investment and policy support in infrastructural-tech development where it has least comparative disadvantage to catch-up with other sub-region regarding industrial output growth. Thus, this study contributes to economic science by filling the gap in the extant empirical literature. However, the study's major limitation is the limited availability of key data in a few SSA countries, which led to the exclusion of these countries. Long-term indicators for human capital skills and infrastructure from Somalia, South Sudan, Seychelles, Uganda, and Zambia were inaccessible. This is an unavoidable limitation.

Notwithstanding, it is pertinent for future studies to work around the study's limitations. Aside from this constraint, the study has contributed to the literature by showing the need to prioritize factor input for industrial sector growth based on the country and sub-regional specifics advantage. Notwithstanding, it is pertinent for future studies to work around the study's limitations.

CHAPTER SIX

THE THRESHOLD AND ASYMMETRIC EFFECTS OF HUMAN CAPITAL SKILLS AND INFRASTRUCTURE ON INDUSTRIAL OUTPUT GROWTH IN SUB-SAHARAN AFRICA.

The purpose of this chapter is to address the third objective of the study, which is:

i) To assess the threshold and asymmetric effects of human capital skills and infrastructure on industrial output growth across sub-regional economic blocs in SSA.

6.1 SUMMARY OF CHAPTER SIX

The threshold and asymmetric effects of human capital skills and infrastructure on industrial output growth have become very important based on the recent clamour for a knowledge-driven economy at the expense of resource-endowed economies across the globe. Therefore, it is pertinent for countries in SSA to align with the recent calls for improved industrial output growth through the complementarity effects of factors-inputs such as human capital skills and infrastructure. In achieving the third object, this study filled notable vacuums in the empirical literature, using panel threshold regression and nonlinear Autoregressive Distributed Lags (NARDL) to ascertain the threshold trajectory and two regimes effects of human capital skills and infrastructure on industrial output growth in SSA. The threshold and asymmetric effects provided different policy options for countries in SSA towards improving industrial output growth, particularly across the sub-regional blocs. Consequently, the study systematically discloses the threshold benchmarks for sustainable industrial output growth in SSA. The study further estimated sub-regional asymmetric effects of human capital skills and infrastructure to disclose the current state of low factor inputs across the sub-regional blocs for proactive policy draft towards improving industrial output growth. Notably, the findings disclosed that the asymmetric effects of human capital skills and infrastructure vary across the sub-regional economic blocs in SSA. Based on these discoveries, an individual region could address its sub-regional specifics through a domesticated policy blueprint to sustain industrial output growth.

6.2 INTRODUCTION

Industry output growth efficiency has drawn varied attention across the academic community. Similarly, the attention of industry practitioners and policy makers has been drawn towards different means of improving industrial sector growth globally (Du et al., 2023). Therefore, it is right for the SSA countries to brace up and develop better means of promoting industrial output within the sub-regions. The study of the nonlinear effect of human capital and infrastructure on industrial output growth is pertinent to providing a better policy guide across the sub-regional blocs in SSA. The study towards this direction appears unique because estimating dual regime effects would provide varied policy options for improved industrial output growth in the sub-region. Notably, studies such as Hongzhong et al. (2018), Ibrahim (2019), Ogunjobi et al. (2021), Harnani et al. (2022), Du et al. (2023), Hao (2023), Özaydin, Özgür and Dağdemir (2023), Mpofu and Nemashakwe (2023), Bouattour et al., (2024) and Njenga (2024) made frantic efforts towards assessing the threshold effects on growth but with less focus from the concepts of this study. Meanwhile, few related studies on human capital and infrastructure such as Stoichev (2014), Keng, Perepelkina, Perepelkinaa, and Morozovaa (2016), Lin, and Orazem (2017), Abdulqadir and Asongu (2021), Okumoko, Omeje, and Udoh (2018), Emily and Muyengwa (2021), Shahrivar et al., (2022), Harnani et al., (2022), Tortorelli et al. (2022) mostly focus on the linear nexus with less attention on the possible nonlinear effect of human capital skills and infrastructure on industrial output growth across SSA. Hence, this study tried to provide a better understanding of nonlinear effects through threshold and NARDL estimating techniques.

Promoting industrial output through human capital skills and infrastructure in SSA is pertinent. Therefore, there is a need to establish better relationships between human capital skills, infrastructure and industrial output growth. Hansen (2011; 2017), Sama et al. (2023) and Alshehry and Belloumi (2024), among scholars, argued that nonlinear relationship in panel data analysis was a better option because of the restrictive nature of linear models in panel data analysis. Consequently, this study chose threshold and asymmetric models over linear models due to the inability of linear models to capture parsimoniously asymmetric effects, which accounted for nonlinear dynamics. Notably, over the years, there have been concerns about why industrial output growth has continued to drop in SSA despite its active and vast human capital populace (Mbonigaba & Akinola, 2019).

Moreover, the reasons for the dwindling industrial sector across the sub-regions might not be far-fetched due to poor human capital potentials and the slow infrastructure spread needed for industrial output growth. Also, considerable wrong empirical tools might have been used in the previous studies without developing better policy options for improving industrial output growth in SSA. Hence, this study attempted to disaggregate the dual regimes' effects of human capital skills and infrastructure on industrial output growth across individual sub-regional economic blocs. This was to account for the true asymmetric effect of human capital skills and infrastructure on industrial output growth across EAC ECCAS, ECOWAS and SADC.

New evidence emerged through the African Development Bank that the African continent's infrastructural spread dwindled despite committing between \$130 and 1\$70 billion annually, with a financing deficit estimated at around \$68–\$108 billion. With this vast financial gap, there is an urgent need to scale up industrial output growth via improved education curriculum design, promoting general infrastructure and improving complementarity approach for indicators of human capital and infrastructure (African Development Bank, 2018; Abdulazeez & Naim, 2018). Hence, it is pertinent for the continent to unleash its potential regarding human capital and infrastructural development for industrial sector growth. Human capital development is mainly deficient in terms of productive skills across the sub-economic region of SSA. Lately, there have been concerns about the poor allocation of resources across different levels of education in SSA (Akinola & Bokana, 2017). For instance, recent reports from the World Bank's bi-annual study on country focus regarding Nigeria showed that authorities in SSA spend the least of its statutory financial outlays on tertiary, secondary, and primary education, despite the country's immense potential regarding human capital composition, that represents twenty per cent (20%) of the entire sub-Saharan African populace. The Nigerian stakeholders have struggled to annex these potentials for productive growth (World Bank, 2018). A well-skilled population is expected to provide the basis for sustainable, productive growth and allow future labour to compete globally in dynamic knowledge-driving economies.

Background information in Figures 6.1 and 6.2 are as follows: Evidence from Figures 6.1 was drawn from four different regions- the European Union (EUN), the North America Euro (NAM), and the Area (ERA) revealed that the sub-Saharan (SSA) lags behind other regions regarding human capital and infrastructural spread towards productive output growth. This is a serious implication for the study and is worth investigating.

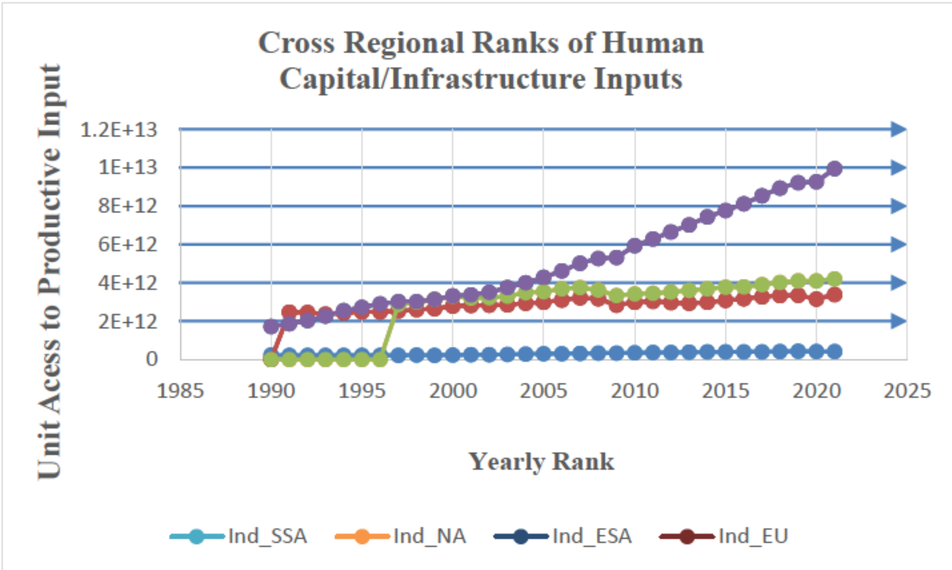


Figure 6.1: Cross Regional Ranks of Human Capital/Infrastructure Inputs

Source: Adapted from the World Bank Development Index (2024).

Figure 6.1 disclosed the comparative rank of cross-region human capital potentials and infrastructural spread in a decade. The trend curve in Figure 6.1 showed that SSA's factor inputs for output growth were low compared to other regions, such as the European Union (EUN), the North American (NAM), and the Euro Area (ERA). Hence, it is glaring that SSA countries lack the potential to propel public goods, such as modern infrastructural techs and productive human capital skills for industrial sector growth. Based on the evidence in Figure 6.1, where the sub-region recorded the least access to productive inputs such as labour with sophisticated skills, access to information communication technology, and accessible transport networks, among others.

Notably, efforts from industrialists across sub-regional blocs in sub-Saharan Africa were low towards identifying and correcting the gaps in human capital skills and infrastructural investments for output growth (Abdulazeez & Naim, 2018; Akinola & Mbonigaba, 2019; Akinlo, 2020). Abdulazeez and Naim (2018) posited the need for SSA countries to devise better means of addressing infrastructural deficiencies and over-reliance on traditional infrastructure funding for improved productive growth. Hence, the rising demand for infrastructure networks to actualize output growth has continuously constrained industrial sector advancement in the sub-region. It is worth noting that human capital potential rolls together with physical capital regarding infrastructure during the production process, which are imperative inputs for industrial advancement for both short-run and long-run growth (Rebelo, 1991 & Mankiw, 1995). However, the policy question would be, for example, what are the threshold and asymmetric effects of human capital skills and infrastructure on industrial output growth directly? It is a common belief that sub-Saharan Africa has a vast population, and investment in that population is vital for industrial output growth (Mbonigaba & Akinola, 2019; World Development Index, 2021).

Hence, it is pertinent to investigate the threshold and asymmetric effects of human capital skills and infrastructure across the sub-regional blocs within SSA. Remarkably, multiple techniques were adopted in the study to validate the results and curb any likely problem inherent in a single-method scenario. Moreover, it is perceptible that most early studies have yet to reveal the threshold and asymmetric effects of human capital skills and infrastructure on industrial output growth, which is one of the contributions of this research.

Consequently, the study is clustered into different sections; section one elucidates the introduction, section two contains the summary of the literature review and the theoretical framework, section three reports the summary of the methodology and the model building, section four explains the empirical analysis and the discussion of the results. In contrast, section five describes the conclusions and the recommendations.

6.3 GAPS AND CONTRIBUTION TO THE LITERATURE

This study contributes to the literature by analyzing the threshold and asymmetric effects of human capital skill and infrastructure development on industrial output growth across sub-regional economies in SSA, using GMM threshold regression and non-linear Autoregressive Distributed Lags (NARDL). Moreover, the study systematically measured the non-linear effects of human capital skills and infrastructure on industrial output growth in SSA. The study adopted a series of pre-estimating techniques such as unit root via ADF and Philip-Peron, correlation matrix and Cross-Section Dependence (CSD) tests to fulfil all the necessary conditions before proceeding on non-linear estimating techniques to ascertain two regimes' effects on human capital skills and infrastructure on industrial output growth across sub-regional blocs in SSA. Studying in this direction paved the way for individual sub-regional policy drafts towards industrial sector advancement by expanding the narrow range of industrial goods across SSA sub-regions.

6.4 THE METHODOLOGY FOR THE ANALYSIS

6.4.1 Justification for the Nonlinear Estimating Techniques

The threshold asymmetric models were chosen over linear models due to the restrictive nature of linear models with the inability to capture parsimoniously asymmetric effects, which accounted for nonlinear dynamics (Odionye & Chukwu, 2023; Woldu & Kanó, 2023). Wald and Likelihood Ratio (LR) tests were conducted to establish the presence of asymmetry in the nonlinear estimating techniques. Analysing the linearity (LR) test established whether there is a nonlinear link between human capital, infrastructure and industrial output growth. Also, the bootstrap method was used to build the P value to test for the threshold significance effect. The GMM threshold asymmetric model was used to test the consistency of the threshold value and the confidence interval of the estimated threshold value (Hansen, 2000; Bouattour et al., 2024). Therefore, the study justified the choice of considering the NARDL model over the ARDL model.

It is pertinent to capture the nonlinear dynamics between human capital skills infrastructural and industrial output growth. This model was chosen over linear models due to the restrictive nature of linear models with the inability to capture parsimoniously asymmetric effects, which accounted for nonlinear dynamics (Woldu & Kanó, 2023). Therefore, the single threshold regression model was modelled thus:

$$Y_t = \theta_1 X_t + U_t \quad q_t \leq \gamma \qquad 3.4.1$$

$$Y_t = \theta_2 X_t + U_t \quad q_t > \gamma \qquad 3.4.2$$

Where $\boldsymbol{Y_t}$ signifies the dependent variable, $\boldsymbol{X_t}$ denotes the independent variable, $\boldsymbol{q_t}$ explained the threshold variable, $\boldsymbol{\gamma}$ accounts for the threshold intensity (quantity), and $\boldsymbol{U_t}$ denotes the stochastic term. The single threshold regression model is (3.4.1, as specified in chapter three), when$\boldsymbol{q_t} \leq \boldsymbol{\gamma}$.

Furthermore, the single threshold regression model is (3.4.2, as specified in chapter three) when$\boldsymbol{q_t} > \boldsymbol{\gamma}$. The indicative function for human capital skills $I(\boldsymbol{HCS_t} \leq \boldsymbol{\gamma}_1)$ is then built. The indicative function for infrastructure $I(\boldsymbol{INF_t} \leq \boldsymbol{\gamma}_1)$ is then built. Therefore, if the conditions in parentheses were met, the value is 1; otherwise, it is 0. Merging the above two formulas brought the following 3.4.3 and 3.4.3, as specified in chapter three:

$$\Delta logIDO_{it} = \theta_1 HCS_{it}\mathrm{I}(HCS_{it} \leq \gamma_1) + \theta_2 HCS_t\mathrm{I}(\gamma_1 < HCS_t < \gamma_2) + \theta_3 HCS_t\mathrm{I}(\gamma_1 > HCS_t) + aw_t + U_t \qquad 3.4.3$$

$$\Delta logIDO_t = \theta_1 INF_t\mathrm{I}(INF_t \leq \gamma_1) + \theta_2 INF_t\mathrm{I}(\gamma_1 < INF_t < \gamma_2) + \theta_3 INF_t\mathrm{I}(\gamma_1 > HCS_t) + aw_t + U_t \qquad 3.4.4$$

Where $\gamma_1 and\ \gamma_2$ denote respective threshold coefficients, and θs explains coefficients of the slope. I(.) is the indicator function. ΔlogIDO explains the industrial output growth, which is denoted as the dependent variable at time t=1, 2, HCSIDO measures the human capital skills-to-industrial output, and INFIDO measures the infrastructure-to-industrial output, which are classified as regime-regressor indicators. w explains the control variables that consist of the gross capital formation-to-industrial output growth and foreign direct investment-to-industrial output growth. U denotes the stochastic error term.

It is worth noting that integrating all variables in the same order is not mandatory using the NARDL model (Shin et al., 2023). Drawing clews from Shin, Yu, Greenwood-Nimmo (2014), Seo et al. (2019), Sama et al. (2023) and Noha and Daniela (2024), the NARDL model is hereby specified thus;

$$logIDO_{i,t} = \beta_0 + \beta_1^{-} logGCF^{-}{}_{i,t} + \beta_2^{+}\mathrm{log}FDI^{+}{}_{i,t} + \beta_3^{-} SER^{-}{}_{i,t} + \beta_4^{+} LIR^{+}{}_{i,t} + \beta_5^{-} logLPR^{-}{}_{i,t} + \beta_6^{+} logLBF^{+}{}_{i,t} + \beta^{-} logACE^{-}{}_{i,t} + \beta^{+} logACT^{+}{}_{i,t} + \beta^{-} logICT^{-}{}_{i,t} + \beta^{+} logAWP^{-}{}_{i,t} + u_{i,t} \ldots\ldots..3.21$$

Where $^{-}$ & $^{+}$ were used to explain the positive and negative partial sums of individual independent variables or the possible effects of different regimes in the NARDL models. Given this, the positive and negative partial sums of the key human capital skills and infrastructure variables were elaborated.

And later harmonised to ***panel models for sub-regional cointegration specifics, thus;***

$$\triangle\, logIDO_i = \beta_0 + \sum_{j=1}^{p} \beta_1 \triangle\, logIDO_{i-1} + \sum_{j=0}^{p} (\beta_2{}^{+} logGCF^{+}{}_{i-1} + \beta_3{}^{-} logGCF^{-}{}_{i-1})$$
$$+ \sum_{j=0}^{p} (\beta_4{}^{+} logFDI^{+}{}_{i-1} + \beta_5{}^{-} logFDI^{-}{}_{i-1}) + \sum_{j=0}^{p} (\beta_6{}^{+} logHCSD^{+}{}_{i-1}$$
$$+ \beta_7{}^{-} logHCSD^{-}{}_{i-1}) + \sum_{j=0}^{p} (\beta_4{}^{+} logINF^{+}{}_{i-1} + \beta_5{}^{-} logINF^{-}{}_{i-1})$$

Where $\sum_{j=1}^{p} \beta_1{}^{+}$ & $\sum_{j=1}^{p} \beta_1{}^{-}$ explained the short-run positive and negative asymmetric effects.

And later harmonised to ***panel models for sub-regional ECM cointegration specifics, thus;***

$$\triangle\, logIDO_i = \beta_0 + \sum_{j=1}^{p} \beta_1 \triangle\, logIDO_{i-1} + \sum_{j=0}^{p} (\beta_2{}^{+} logGCF^{+}{}_{i-1} + \beta_3{}^{-} logGCF^{-}{}_{i-1})$$
$$+ \sum_{j=0}^{p} (\beta_4{}^{+} logFDI^{+}{}_{i-1} + \beta_5{}^{-} logFDI^{-}{}_{i-1}) + \sum_{j=0}^{p} (\beta_6{}^{+} logHCSD^{+}{}_{i-1}$$
$$+ \beta_7{}^{-} logHCSD^{-}{}_{i-1}) + \sum_{j=0}^{p} (\beta_4{}^{+} logINF^{+}{}_{i-1} + \beta_5{}^{-} logINF^{-}{}_{i-1}) + \theta ECT_{\mathrm{i}} + U_{\mathrm{i}}$$

θ captures the coefficient of the error correction term-ECT that explains the speed of adjustment from the point equilibrium in the short run under a certain lag length criterion estimated in the NARDL model to the point of equilibrium in the long run. The rule of thumb is that it is expected that the value of ECT must be negative and fall between 0 and 1 in absolute value. The justification for exploring harmonised panel models over the generic models was to accurately account for individual sub-regional specifics among EAC ECCAS, ECOWAS, and SADC through indicator (s) that have proven to be the close measures of the explanatory variables and consistent with the level significant effects.

6.5 DATA ANALYSIS

This section of our study addresses the pre-estimation statistics, empirical analysis, post-estimating tests, and study findings. For example, the pre-estimation results comprise the trend analysis, mean distribution statistics, descriptive analysis, correlation matrix, unit root test and lag length criteria. The empirical segment consists of the threshold regression analysis, Nonlinear-Autoregressive Distributed Lags (NARDL) and post estimations results.

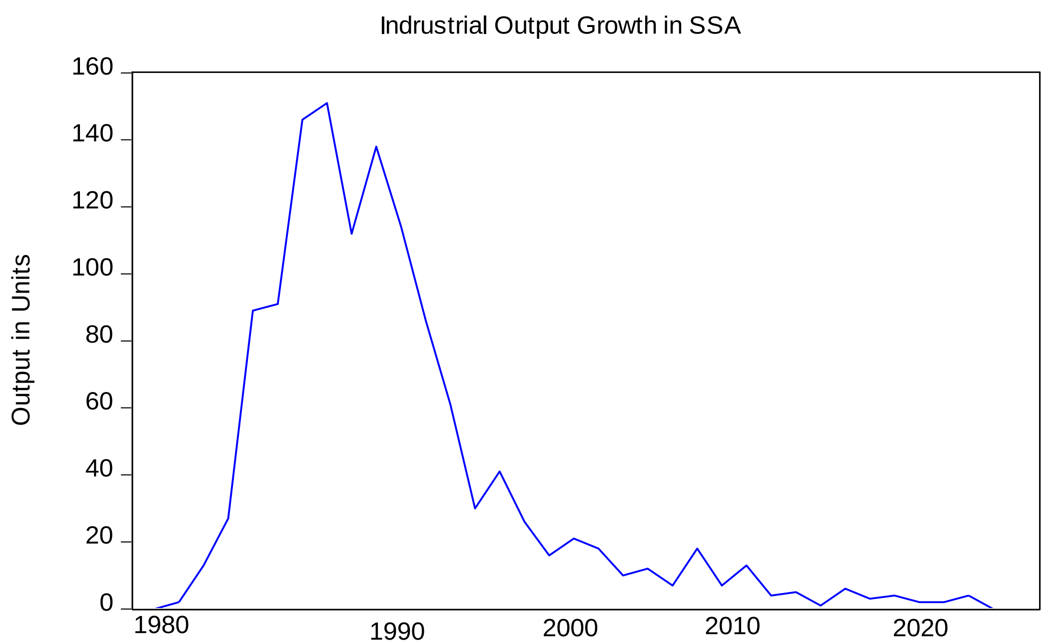


Figure 6.2: **Industrial Output Trend across Sub-Saharan Africa (SSA)**

Source: Author's Computation, (2024).

The trend analysis report in Figure 6.4 showed the continuous fall in productive growth across sub-Saharan Africa. The sub-region recorded rising industrial output growth between the early '80s and early '90s. However, the SSA region's productive strength persistently nosedived from 2000 to 2021. Hence, the outcome of this nature calls for serious attention, which necessitates this study. Also, the study looks inwardly to account for the average sub-regional industrial output growth. The motive behind this is to fill the gap in the literature in this direction firstly and secondly to ascertain individual sub-regional specifics and perennial problems, as this attempt would guide our policy recommendations relevant to individual economic blocs in achieving industrial sector growth. Mean industrial output based on sub-regional performance showed that ECCAS and SADC were better off than other sub-regions like ECA and ECOWAS. In Figure 3, the mediating roles of governance influence output growth performance via human capital and infrastructure development in ECCAS communities, SADC groups, ECA blocks, and ECOWAS sub-regions.

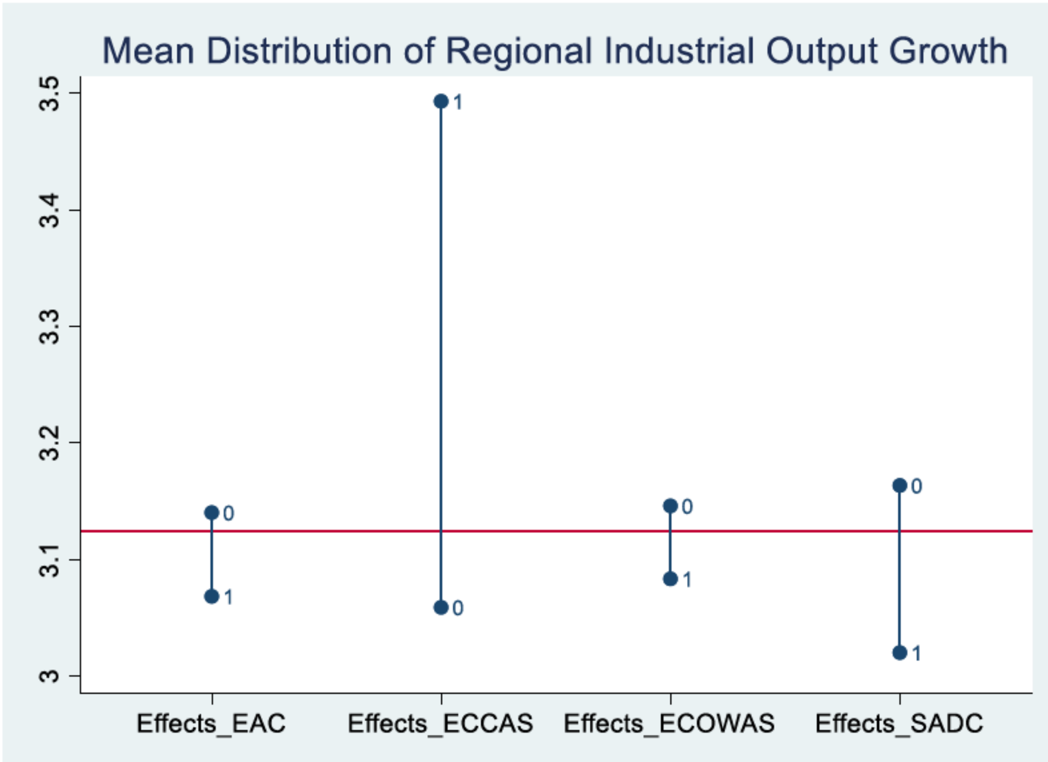


Figure 6.3: Mean classification of Sub-regional industrial Output Growth in SSA

Source: Author's Computation, (2024).

Meanwhile, Table 6.1 shows the descriptive statistics of the explained and the explanatory variables across 1280 observations employed in the study. The indicators for gross capital formation (GCF), foreign direct investment (FDI) and school enrolment rate (SER) have the least minimum statistics with -81.7722, -26.6384, and -.053553, respectively. While the variables for labour participation rate (LPR), access to water (AWP), and labour force (LBF) have the most minimum statistics with 42.39, 0.414847, and 1.8993, respectively. Among all the explanatory variables, school enrollment has the least mean of 0.8818541 school enrolment rate (SER). This further reveals the problems associated with the sources of human capital skill development due to poor curriculum design, which implies their productive skill. On the other side, infrastructure has a 2.272217 mean, which implies the lowest mean for infrastructure development across SSA. The implication of this nature calls for serious attention, as the spread of information technology in SSA still needs to catch up to other emerging economies, hence slow industrial sector growth. Alternative means by which skilled labour and improved infrastructure can be accumulated regarding rapid investment in the industrial sector still lag behind as the data for foreign investment pooled 3.274744 mean throughout the thirty-two years under review. Hence, a low average industrial output was produced throughout the period, with 3.124073 units. The descriptive statistics show that low productive skills and infrastructure cause low industrial sector growth due to the poor education system and poor policy options in creating an environment for rapid industrial growth in SSA.

Table 6.1: **Descriptive Statistic**

Variable	**Mean**	**Std. dev.**	**Min Max**	**A Priori Expectations**
LOGIDO	3.1241	0.47554	1.5164 4.4349	-
SER	0.8819	0.1525	-0.0536 1.4827	Positive
LPR	68.5362	11.7612	42.39 92.49	Positive
LOGLBF	14.8577	1.5435	1.8993 17.9744	Positive
GCF	9.8966	29.9314	-81.7722 507.953	Positive
FDI	3.2747	7.7170	-26.6384 161.824	Positive
LIR	59.2043	22.1698	0 101.473	Positive
ICT	2.2722	4.6449	0 37.6405	Positive
ACE	36.6379	24.6640	0.5338 100	Positive
ACT	20.7262	15.8749	0.1258 79.4936	Positive
AWP	14.1705	44.3200	0.4149 761.1115	Positive

Source: Author's Computation, (2024).

The correlation results in Table 6.2 disclosed that our variables are free from the multi-collinear problem, as none of the interactive coefficients among the variables returned as absolute figures of one, but they were weak and mostly less than Figure 1. In fact, most of the correlation coefficients between industrial output growth and the explanatory indicators returned as negative. This outcome contradicts our apriori expectation in Table 6.1, which requires attention. According to the endogenous growth theory, a unit rise in labour and capital input is expected to bring about a unit rise in output growth. However, SER, FDI, and ACT indicators conformed to our theoretical expectation but with very weak coefficients. This is an implication for poor complementarity use of factor inputs such as school enrolment (SER) and access to transportation (ACT) that could attract sustainable foreign direct investment (FDI) for industrial output growth.

Meanwhile, the unit root test was conducted to disclose the possible presence of unit roots in the panel data set in SSA. Other necessary pre-condition tests were conducted to justify the study's asymmetric analysis. A study of this nature would allow us to propel industrial output growth through the dual effects of human capital skills and infrastructure.

Table 6.2: **Correlation Matrix**

Var.	LOGIDO	GCF	FDI	SER	LIR	LPR	LOGLBF	ACE	ACT	ICT	AWP
LOGIDO	1.0000										
GCF	-0.019	1.0000									
FDI	0.132	0.124	1.0000								
SER	-0.047	-0.033	0.019	1.0000							
LIR	0.334	-0.059	0.059	0.468	1.0000						
LPR	-0.075	0.032	0.004	-0.149	-0.045	1.0000					
LOGLBF	-0.007	-0.026	-0.042	-0.150	-0.118	0.476	1.0000				
ACE	-0.047	-0.079	-0.048	0.269	0.226	-0.249	0.028	1.0000			
ACT	0.024	0.025	0.058	0.091	-0.049	0.037	0.020	0.064	1.0000		
ICT	-0.090	-0.080	-0.032	0.074	0.041	-0.298	0.130	0.639	-0.036	1.0000	
AWP	0.249	0.042	0.014	-0.025	0.069	0.013	-0.075	-0.032	-0.069	-0.074	1.0000

Source: Author's Computation, (2024).

Table 6.2 informs us of the potential association-ship among the estimating variables, especially between dependent and independent variables. Notably, the negative and weak correlation outcomes among the series justify our arguments under the problems statement, reflecting the situation concerning poor industrial output growth in SSA. Industrial output exhibited a negative correlation with school enrolment rate. Similarly, among the ten regressors, indicators for labour participation rate, labour force, access to transportation and gross capital formation disclosed a negative correlation with industrial output growth. This might be connected with various dynamic effects of low productive skills and poor infrastructural spread in sub-Saharan Africa. Interestingly, the correlation coefficient among the independent variables is positive and negative but primarily weak, meaning that the data are free from the potential incidence of multicollinearity.

Table 6.3: **Unit Root Tests**

Variables @ Levels	**ADF. Statistic @ Level**	**P-value**	**P.Peron Statistic @ Level**	**P-value**	**Variables @ First Diff.**	**ADF. Statistic @ First Diff.**	**P-value**	**P.Peron Statistic @ First Diff.**	**P-value**
logIDO	-102.268	0.0474	-139.243	0.0000	D.LogIdo	-467.328	0.0000	-867.855	0.0000
GCF	-410.767	0.0000	-791.918	0.0000	D.GCF	-996.989	0.0000	-1025.45	0.0000
FDI	-140.432	0.0000	-232.713	0.0000	D.FDI	-471.980	0.0000	-4947.76	0.0000
SER	-134.791	0.0001	-461.499	0.0000	D.SER	-747.054	0.0000	-3192.12	0.0000
LIR	-199.764	0.0000	-273.773	0.0000	D.LIR	-433.428	0.0000	-2880.62	0.0000
LPR	-72.0805	0.7240	-62.5596	0.9251	D.LPR	-107.052	0.0234	-143.040	0.0000
logLBF	-45.8591	0.9992	-31.6632	0.9998	D.LogLBF	-59.3227	0.0097	-545.674	0.0000
ACE	-114.039	0.0075	-276.956	0.0000	D.ACE	-474.837	0.0000	-3167.00	0.0000
ACT	-83.6757	0.2069	-94.0219	0.0581	D.ACT	-298.995	0.0000	-901.214	0.0000
ICT	-32.2013	0.9996	-24.6984	0.9999	D.ICT	-282.505	0.0000	-536.737	0.0000
AWP	-433.899	0.0000	-1366.10	0.0000	D.AWP	-657.742	0.0000	-9686.43	0.0000

Source: Author's Computation, (2024).

Table 6.4: **Lag Selection Criteria**

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-34926.96	NA	1.23e+35	109.1780	109.2477	109.2051
1	-25370.85	18783.73	1.81e+22	79.62767	80.39448	79.92530
2	-24978.23	759.4806	7.25e+21*	78.71322*	80.17714*	79.28144*
3	-24900.77	147.4248	7.78e+21	78.78364	80.94466	79.62244
4	-24819.39	152.3194*	8.25e+21	78.84185	81.69998	79.95123

** 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.*

Based on the unit root reports in Tables 6.3 and 6.4, the dynamics of Nonlinear Autoregressive Distributed Lags (NARDL) modelling stated that all series must be stationary at level i.e. I(0) or at first difference i.e. I(1) following a particular lag length orders (Im, Pesaran & Shin, 2003; Hlouskova & Wagner, 2005; Hurlin & Mignony, 2006; Ramalingam & Gangai, 2020; Martha Matashu & Melikhaya Skhephe, 2022). No series should be integrated at the second difference to avoid spurious estimation, i.e. I (2). The Philip Peron and Augment Dicey-Fuller cross-sectional tests were used to ascertain that there was no presence of I (2) order of integration among the series. Therefore, the independent time series must be integrated in order, I (1) (Bokana & Akinola, 2017; Kayamo, 2021; Sama et al., 2023). It can be observed that the series were stationary at both levels and after the first differencing. This showed that all indicators for human capital skills, infrastructure and industrial output growth were free from any form of unit root and were suitable for statistical analysis. Notably, based on our stated objective three, it is pertinent for us to perform threshold analysis, as argued by Seo, Kim and Kim (2019). This is to reveal the threshold effects of human capital skills and infrastructure on industrial output growth in SSA.

6.6 THE BASELINE OUTCOMES OF PANEL GMM THRESHOLD EFFECT OF HUMAN CAPITAL AND INFRASTRUCTURE ON INDUSTRIAL OUTPUT GROWTH IN SSA.

Interestingly, the individual indicator's fixed effects were eliminated using the dynamic panel GMM model through forward orthogonal deviation transformation (Arellano and Bover, 1995; Ndoricimpa, 20217). This would ensure that the stochastic terms were not auto-correlated. Therefore, the cross-sectional threshold model is in line with LR outcomes. The likelihood ratio (LR) statistic was used to test the consistency of the threshold value and how the confidence interval of the estimated threshold density was achieved through the dynamic panel model (Caner and Hansen, 2004; Ndoricimpa, 2017; Hansen, 2000; Woldu & Kanó, 2023; Bouattour et al. 2024). Also, the critical values of 95% level at the confidence interval for the threshold of the likelihood ratio (LR) statistic is expressed along the compact threshold models (3.18 & 3.19) from threshold regression models (3.17 & 3.18) in chapter three. Therefore, in Table 6.5, the sample observations were divided into three groups with human capital skills and infrastructure intensities as the threshold variables, which were low human capital intensity (HCS < 33.6), medium human capital skills intensity (25.3 < HCS < 33.6), and high human capital skills intensity (HCS > 25.3). Also, low infrastructure intensity (INF < 33.6), medium infrastructure intensity (25.3 < INF < 33.6), and high infrastructure intensity (INF > 25.3) were analyzed in line with the panel regression estimating techniques suggested by Shin (2016) and Kim and Kim (2019). Also, the estimated outcomes for individual compacted models were reported in Table 6.5**.**

Table 6.5: **Panel GMM Threshold Results**

Estimated human Capital Skills and Infrastructure threshold			**Units**	
			29.43	
95% confidence interval			25.28568 33.58251	
Dependent-threshold			Regressors	
Estimated Coefficients			Standard Error(s)	
Threshold 1 0.663			0.083	
Threshold 2 -0.132			0.145	
Joint threshold effect of independent			**Regressors**	
Estimated Coefficients in Two Regimes			**Standard Error(s)**	
Variable(s)	Low	High	Low	High
SER	-2.757	-11.299 **	3.462	5.528
LIR	0.011	-0.245***	0.014	0.052
LPR	-0.073	-0.579**	0.302	0.271
LogLBF	2.590***	-1.020***	0.006	0.003
ACE	0.048*	-0.139***	0.028	0.053
ACT	0.005	-0.082	0.020	0.062
ICT	-0.167	2.79***	0.353	0.648
AWP	0.022***	-0.022***	0.005	0.006
(Control Variables)				
GCF	-0.004	0.120*	0.061	0.067
FDI	0.154	-0.1496628	0.154	0.067

Source: Author's Estimations (2024) are in line with Shin's (2016) and Kim and Kim's (2019) Stata Codes. ***Note:*** *(***), (**), and (*) indicate 1%, 5% and 10% levels of significance, respectively. N = 40, T = 32, Panel Var. = c_id, Time Var. = years, Number of moment conditions = 735*

Consequently, the findings suggest the presence of human capital skills and infrastructure threshold of 29.43 units for SSA at a 95% confidence interval at (25.28568 33.58251). The results established nonlinear effects of human capital skills and infrastructure on industrial output growth across SSA. Notably, the estimated coefficients of human capital skills and infrastructure such as school enrolment rate-SER, literacy rate-LIR, labour participation rate-LPR, log of labour force-logLBF, access to energy-ACE, access to transportation-ACT, information technology-ICT and access to water-AWP were positive and negative across the two regimes of threshold points. For example, logLBF and AWP were positive and statistically significant at (1% level), respectively, to influence industrial output growth when units of input from human capital skills and infrastructure through labour force and access to water were below and above the threshold. The two indicators disclosed positive and significant effects on industrial output growth at a lower threshold. That is, a unit rise in the labour force and access to water brought about a 2.59 and 0.02 units increase in industrial output growth. However, human capital skills and infrastructure contributions to industrial output growth via LogLBF and AWP were negative and significant at (1% level) in the higher regime, i.e. about 1.02 and 0.02 units of input fall in industrial output growth were caused by human capital and infrastructure via labour force and access to water when the units of input are above 29.43 thresholds. This implied that the effect of LogLBF and AWP on industrial output growth becomes detrimental to output growth when it exceeds the 29.43 threshold, which is a contraction with apriori expectations.

Similarly, the indicators for human capital skills via school enrolment, literacy, and labour participation rates were negative and significant (at a 1% level) to impact industrial output growth in the higher threshold regimes. That is, a unit increase in enrolment rate, literacy rate and labour participation rate caused about 11.29, 0.25 and 0.58 fall in industrial output growth, respectively. This effect contradicted apriori expectations of industrial output growth above the threshold point, which implies poor human capital skills contributions to industrial output growth across SSA. Furthermore, the threshold effect of infrastructure on industrial output growth through access to energy and transportation disclosed adverse and significant non-linear effects below the threshold across SSA. That is, a unit rise in access to energy and transportation brought about a 0.14 and 0.08 fall in industrial output growth.

Meanwhile, at higher regimes, the infrastructure indicators via access to energy and transportation disclosed a negative and significant impact on industrial output growth in SSA. That is, a unit rise in access to energy and transportation brought about a 0.14 and 0.08 fall in industrial output growth above the threshold point. These outcomes contradicted the expected economic intuition of positive relationships, which implies poor infrastructural spread across the sub-region. The control variables, such as gross capital formation-GCF and foreign direct investment-FDI, were not statistically significant at the lower threshold. While only gross capital formation-GCF disclosed a significant effect (at a 10% level) at higher threshold. This implied that massive local investment in locations and localizations of industries were more proactive at the higher threshold to cause a change in industrial output growth. Hence, the SSA sub-regions need to set a production target above the units of threshold alongside an appropriate policy draft that addresses negative significant effects for improved industrial output growth.

Consequently, threshold effects were more effective at a higher regime. That is, SSA countries need to strive and invest more in the indicators of human capital skills development and infrastructure development to have sustainable industrial output growth. Setting the input unit below the 29.43 unit threshold would further slow industrial sector growth at the sub-regional level.

Key Explanatory Variable Specifics: The threshold effect of human capital skills development on industrial output growth.

There is a need to estimate the direct threshold effect of human capital skills development on industrial output growth, all things being equal. This is to provide necessary policy direction for countries in SSA and to indicate which factor inputs (human capital skills or infrastructure) must be prioritised for industrial output growth in SSA.

Table 6.6: **Effect of Human Capital Skills-industrial Output Growth Threshold**

Estimated Human Capital Skills-industrial Output Growth Threshold	**Units**
γ	28.93
95% confidence interval	20.48963 37.36661

Threshold effect of independent			**Regressors**	
Estimated Coefficients in Two Regimes			**Standard Error(s)**	
Variable(s)	Low	High	Low	High
SER	6.189	-9.412*	5.460	0.006
LIR	-0.062***	-0.037***	0.022	0.009
LPR	-0.013	0.039	0.109	0.109
LogLBF	-2.065	2.121	0.538	0.828

Source: Author's Estimations (2024) are in line with Shin's (2016), Seo et al.'s (2019) and Kim and Kim's (2019) Stata Codes. ***Note:*** *(***), (**), and (*) indicate 1%, 5% and 10% levels of significance, respectively. N = 40, T = 32, Panel Var. = c_id, Time Var. = years, Number of moment conditions = 615*

Notably, findings from the specific threshold model suggest the presence of a human capital skills threshold of 28.93 units for SSA at a 95% confidence interval at (20.48963 37.36661). The results established nonlinear effects of human capital skills on industrial output growth across SSA. The estimated coefficients of human capital skills such as school enrolment rate-SER, literacy rate-LIR, labour participation rate-LPR and log of labour force-logLBF were mixed (i.e. positive and negative) across the two regimes of threshold points. For example, labour force-logLBF was positive and statistically significant at (1% level) in influencing industrial output growth when units of input from human capital skills through labour force-logLBF are above the threshold. However, human capital skills contribution to industrial output growth via labour force-LogLBF was negative and significant at (1% level) in the low regime, i.e. about 2.07 units of input fall in industrial output growth was caused by human capital via labour force when the units of input are below 28.93 thresholds. This implies that human capital skills affect industrial output growth and become detrimental to output growth when it is below the 28.93 threshold point. The results were consistent with the outcomes from the joint threshold model. Contrary to economic apriori expectations, school enrolment negatively and significantly affected industrial output growth above the 28.93 units' threshold. This outcome was in line with the joint model outcome, indicating SSA's poor human capital skills composition.

Meanwhile, an indicator for human capital skills via literacy rate was negative and significant (at 1% level) to impact industrial output growth in the two threshold regimes. This implies poor human capital skills contributions to industrial output growth across SSA. Data for labour participation rate was positive and insignificant across lower and higher regimes of the threshold. This might be connected to mismatched skills possessed by labour supply in the SSA market. The poor curriculum design across SSA's schools and education sector might be responsible for the negative threshold effect on industrial output growth.

Key Explanatory Variable Specifics: The threshold effect of infrastructure development on industrial output growth.

As it was earlier stated under the specific model for human capital skills. Estimating the direct threshold effect of infrastructure development on industrial output growth is pertinent, all things being equal. This is to provide a necessary policy guide for countries in SSA and to indicate which factor inputs (human capital skills or infrastructure) need to be prioritised for industrial output growth in SSA.

Table 6.7: **Effect of Infrastructure-Industrial Output Growth Threshold**

Estimated Infrastructure-industrial Output Growth Threshold			**Units**	
γ			31.12	
95% confidence interval			23.7854 38.45595	
Threshold effect of independent			**Regressors**	
Estimated Coefficients in Two Regimes			**Standard Error(s)**	
Variable(s)	Low	High	Low	High
ACE	-0.019	0.098***	0.015	0.024
ACT	-0.037***	0.046***	0.014	0.010
ICT	0-.099	0.556	0.289	0.394
AWP	-0.006	0.009	0.006	0.007

Source: Author's Estimations (2024) are in line with Shin's (2016) and Kim and Kim's (2019) Stata Codes. ***Note:*** *(***), (**), and (*) indicate 1%, 5% and 10% levels of significance, respectively. N = 40, T = 32, Panel Var. = c_id, Time Var. = years, Number of moment conditions = 615*

Notably, findings from the specific threshold model suggest an infrastructure threshold of 31.12 units for SSA at a 95% confidence interval at (23.7854 38.45595). The results established the nonlinear effects of infrastructure on industrial output growth across SSA. The threshold effect of infrastructure on industrial output growth exhibited significant positive and negative effects across the two regimes of a threshold. For example, measures of infrastructure through access to energy, water resources and information technology were negative and insignificant below the threshold of 31.12 units. Infrastructure contributions through access to energy, water resources, and information technology were ineffective at the lower threshold regime, with their respective input units at about 0.02, 0.01, and 0.09.

Meanwhile, the contribution of infrastructure through access to transport was significant across the two regimes of thresholds. The indicator for transportation exhibited a negative and significant effect on industrial output growth at the lower threshold and possessed a positive and significant impact at the upper threshold. This was an indicative effect on industrial output in the sub-region. Consequently, the sub-region must target infrastructural unit input above 31.12 units to sustain industrial output growth. These outcomes were consistent with the outcomes from the joint model. Similarly, access to energy was disclosed to be positive and statistically significant at (1% level) above the unit threshold. A unit improvement in transportation networks brought about a 0.05 increase in industrial output growth above the threshold point.

Generally, the infrastructure threshold outcomes disclosed the dilapidated infrastructural spread in SSA. The negative and significant impact of key infrastructure on industrial output signals poor infrastructural spread across the sub-region, which is an implication for this research. Based on the outcomes in Table 6.7, this study has provided the needed direction towards improving industrial output growth. The decision on which infrastructure indicators should be prioritised is now clear.

The threshold effect of control factors for human capital and infrastructure on industrial output growth.

It was justified under the specific models for human capital skills and infrastructure. It is pertinent to estimate the threshold effect of exogenous factors (gross capital formation and foreign direct investment) on industrial output growth, all things being equal. This is to provide a necessary policy guide for countries in SSA and to demonstrate how these factors exogenously contributed to industrial output growth in SSA.

Table 6.8: **Effect of Control Factors-industrial Output Growth Threshold**

Estimated Control Variables-industrial Output Growth threshold			**Units**	
γ			31.79	
95% confidence interval			20.48963 37.36661	
Threshold effect of independent			**Regressors**	
Estimated Coefficients in Two Regimes			**Standard Error(s)**	
Variable(s)	Low	High	Low	High
GCF	0.064	-0.007**	0.008	0.003
FDI	0.027	-0.061**	0.034	0.029

Source: Author's Estimations (2024) in line with Shin (2016) and Seo et al. (2019), Kim and Kim (2019). ***Note:*** *(***), (**), and (*) indicate 1%, 5% and 10% levels of significance, respectively. N = 40, T = 32, Panel Var. = c_id, Time Var. = years, Number of moment conditions = 615*

Notably, findings from the specific threshold model of gross capital formation and foreign direct investment suggest the presence of a threshold of 31.79 units for SSA at a 95% confidence interval at (28.26826 35.32235). The results established nonlinear effects of gross capital formation and foreign direct investment on industrial output growth across SSA. To achieve industrial sector growth, an encompassing production threshold target must be set above 31.79 units of input across the sub-region. For example, massive local and foreign direct investment targets above the upper threshold are pertinent towards sustaining industrial output growth across the sub-region. Gross capital formation and foreign direct investment data disclosed significant positive and negative effects across the two threshold points. That is, a unit in local investment through massive gross capital formation brought about a 0.01 increase in industrial output growth above the threshold. Also, a unit rise in foreign direct investment brought a 0.06 decrease in industrial output growth above the threshold point. This meant that some form of regulation should moderate the flocks of FDI within the sub-region to curb possible crowd-out effects and incidence of capital flight. Aside from those concerns, gross capital formation and foreign direct investment were better control factors for industrial output growth in SSA.

6.7 THE NON-AUTOREGRESSIVE DISTRIBUTED LAGS (NARDL) ESTIMATION

Based on the unit root reports in Tables 6.3 and 6.4, the dynamics of Non-linear Autoregressive Distributed Lags (NARDL) estimating techniques were fulfilled. Hence, the panel NARDL outcomes were reported across the sub-regional blocs in SSA. An informed representation of the two key independent variables was made using harmonized panel models, and NARDL outcomes were reported across sub-regional blocs. The indicators for human capital were represented by school enrolment rate-SER being the primary source of human capital skill acquisition, and access to energy-ACE represented the primary source of infrastructure spread. These indicators better explain HCSD and INF with consistent levels of significance. Moreover, representation through harmonized models was necessary because the data for SER and ACE disclosed high levels of asymmetric effects, and they form major sources of human skills development and infrastructure development in SSA.

Table 6.9: **Harmonized Panel NARDL Results across EAC**

Panel Regressors	**Co-efficient**	**T-statistics**	**P-value**
Dep. Variable LogIdo			
Long-Run Panel			
(LOGIDO(-1))	-0.0153	-2.1786	0.0586*
HCSD (i.e. SER)$^{-}$	3.1572	1.0566	0.2927
HCSD (i.e. SER)$^{+}$	1.7287	3.8206	0.0002***
INF (i.e. ACE)$^{-}$	0.0262	0.8463	0.3990
INF (i.e. ACE)$^{+}$	-0.8032	-7.8699	0.0000***
HCSD (i.e. SER(-1))$^{-}$	-1.1909	-3.0176	0.0112***
HCSD (i.e. SER(-1))$^{+}$	-0.0509	-2.3456	0.0304**
INF (i.e. ACE(-1))$^{-}$	0.0115	0.1077	0.9144
INF (i.e. ACE(-1))$^{+}$	-0.0214	-1.9332	0.0736*

Short-Run Panel:			
D(LOGIDO(-1))	0.108989	1.0645	0.2896
HCSD (i.e. DSER)$^{-}$	0.3012	1.8642	0.0921*
HCSD (i.e. DSER)$^{+}$	-0.3596	-0.5409	0.5897
INF (i.e. DACE)$^{-}$	-0.0110	-3.9147	0.0089**
INF (i.e. DACE)$^{+}$	0.0868	2.7826	0.0300**
GCF (1st Control var.)	-0.0002	-0.3017	0.7635
FDI (2nd Control var.)	0.0204	2.3460	0.0331**
C	3.3360	59.4625	0.0000***
ECM(-1)	-0.4739	-2.2073	0.0321**
R-squared	0.8406	F-statistic	16.3086
Adj. R-squared	0.8001	Prob.	0.0000
Durbin-Watson stat.	2.0307		

Source: Author's Estimations (2024). This is in line with Shin and Greenwood-Nimmo (2014), *Shin (2016).* ***Note:*** *(***), (**), and (*) indicate 1%, 5% and 10% levels of significance, respectively.*

Explanation of the Asymmetric results in EAC

It has been observed that the indicators of human capital skills and infrastructure disclosed dual effects through a positive and negative shift in industrial output growth across the East African Community Economic (EAC) bloc in SSA. A positive human capital skills and infrastructure shift led to increased industrial output growth in the EAC sub-region. In another direction, a negative human capital and infrastructure shift leads to increased industrial output growth in the EAC sub-region. This finding emphasised the asymmetric effect of human capital skills and infrastructure on industrial output growth in EAC. Based on the long-run outcomes, a positive change in human capital skills via school enrolment rate-SER caused about 1.729 units increase in industrial output growth at 1% significance level in the East African Community economy (EAC). In contrast, a negative shift in human capital has an insignificant effect on EAC's industrial output growth. Also, a positive shift in infrastructure spread through access to energy caused a 0.803 unit fall in industrial output growth at a 1% significance level in the East African Community Economic (EAC) bloc.

In contrast, an adverse change in infrastructure has no significant effect on EAC's industrial output growth. The lag effect of human capital proved to be more significant across the two regimes than infrastructure. That is, a positive change in the lag of human capital skills through school enrolment rate-SER caused about 0.051 units to drop in industrial output growth at a 1% level of significance, while a negative shift in the lag of human capital via SER caused about 3.018 falls in industrial output growth at 5% level of significant in EAC. Also, a positive change in the infrastructure lag through access to energy caused about 0.021 units of fall in industrial output growth at a 10% significance level in EAC.

According to the short-run results, it was disclosed that human capital skills and infrastructure exhibited two regimes' effects on industrial output. The infrastructure measure on industrial output showed better dual effects than human capital skills in the short run. For example, a positive rise in infrastructure caused about 0.011 units to fall in industrial output at a 5% significance level in the short run across EAC. Also, a negative change in infrastructure caused about 0.087 increase in industrial output growth at a 5% significance level in the short run across EAC. Meanwhile, a negative fall in human capital skills brought about a 0.301 units rise in industrial output growth at 10% level of significance in the short run, while a positive shift in human capital skills had an insignificant effect on industrial output growth. The control variable through foreign direct investment (FDI) disclosed some magnitude of influence on industrial output growth. A unit rise in foreign direct investment exogenously caused about 2.35 units to rise in industrial output growth at a 5% significance level across EAC. Control factors such as gross capital formation exogenously disclosed an insignificant impact on industrial output growth in EAC.

Table 6.10: **Long-run and Short-Run Asymmetry Results**

Sub-Region	Wald Test	F-statistic	P-value	Decision (Inferences)
EAC	W_{LR_un}	13.6070***	0.0035	Asymmetric
	W_{SR_un}	5.7951**	0.0176	Asymmetric

Note: *WLR_un denotes the long-run asymmetric estimation; WSR_un captures the short-run asymmetric estimation; ***, **and * signifies significance at 1%, 5% and 10% level.*

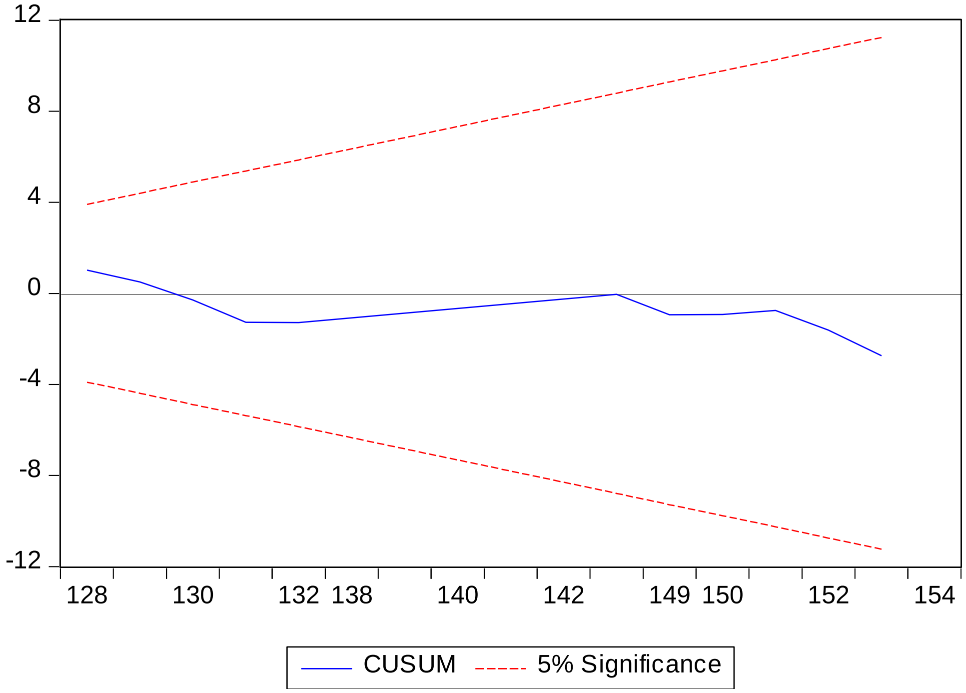


Figure 6.4: CUSUM Test for EAC

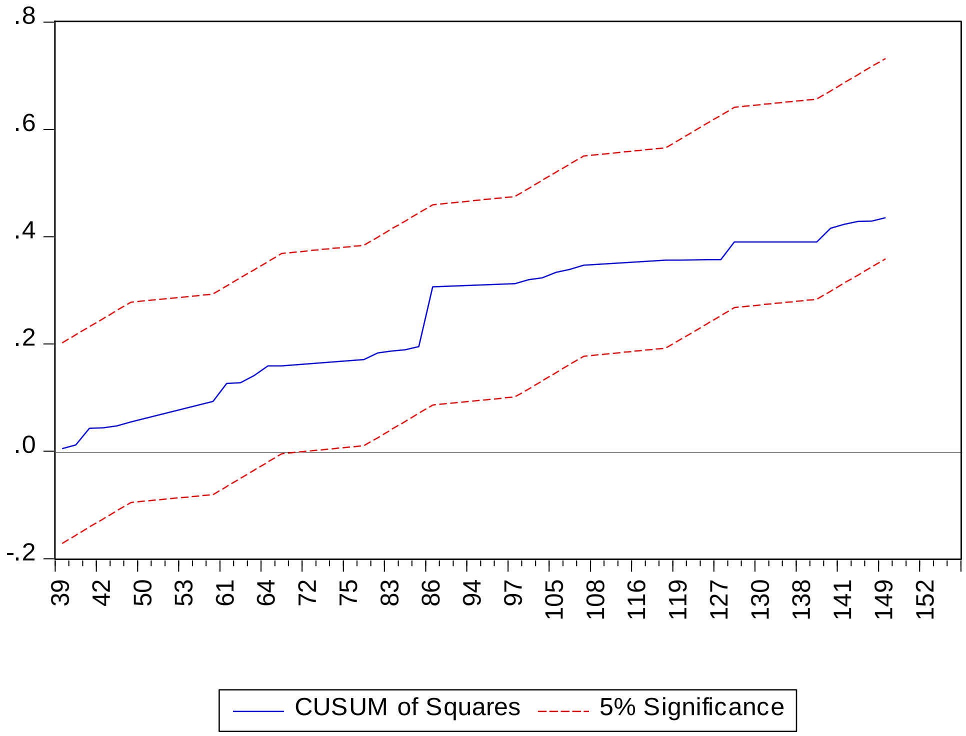


Figure 6.5: CUSUM Square Test for EAC

Table 6.11: ***Padroni's Panel Cointegrating Reports for EAC***

within-dimension	Statistic	Prob.	Between-dimension	Statistic	Prob.
rho	-0.091294	0.4636	G-rho	2.020512	0.9783
PP	-4.565425	0.0000***	G-PP	-2.880381	0.0020***
ADF	-6.271422	0.0000***	G-ADF	2.560302	0.0120**

Source: *Author's Computation (2024).* ***Note:*** *The long-run cointegration estimation was denoted by symbols ***, **and *, which signifies significance levels at 1%, 5%, and 10%. Included observations: 83, Cross-sections included: 8. Null Hypothesis: No cointegration.*

Generally, the NARDL model for the EAC sub-region exhibited both long-run and short-run dual effects of human capital skills and infrastructure on industrial output growth. Remarkably, the Error Correction Model (ECM) coefficient disclosed a high speed of adjustment between the short-run and the long-run at 47%. The specified models react quickly to any disruption at the equilibrium point. Similarly, the F-statistic showed that the EAC NARDL model was statistically significant in predicting the dual effect of the key variables. The R-square at 0.840561 showed the level of variation in independent variables that explained the dependent variable. The indicators of human capital skills and infrastructure explained 84% variation in industrial output growth in EAC. The Durbin-Watson (DW) coefficient showed about 2.031, indicating the absence of positive and negative autocorrelation in the overall model.

The diagnostics results further validated the empirical findings that disclosed the asymmetric effect of human capital skills and infrastructure on industrial output growth in EAC. Based on the Wald statistic outcomes, the null hypothesis of symmetric effect was rejected for both long-run and short-run. The Wald coefficients established the valid asymmetric effect of human capital skills and infrastructure on industrial output growth in EAC. Lastly, the CUSUM and CUSUM square curves revealed that the specified models were stable. The next step is to analyze the asymmetry of human capital skills and infrastructure regarding industrial output growth in ECCAS.

The cointegrating statistic disclosed different levels of cointegration across different estimating inferences. Notably, the null hypothesis of no cointegration among the panel dataset for the

NARDL model can be firmly rejected. This is because two inference tools reveal some levels of cointegration within and between dimensions. For example, Philip-Peron (PP) and Augmented Decay-Fuller statistics demonstrated some levels of cointegration at 1% and 5% significant levels across the two cross-sections. The next step is to analyze the asymmetric effect of human capital skills and infrastructure regarding industrial output growth in ECCAS.

Table 6.12: **Harmonized Panel NARDL Results across ECCAS**

Panel Regressors	**Co-efficient**	**T-statistics**	**P-value**
Dep. Variable LogIdo			
Long-Run Panel			
(LOGIDO(-1))	-0.2181	-3.5129	0.0006*
HCSD (i.e. SER)$^{-}$	-2.3506	-0.8510	0.3979
HCSD (i.e. SER)$^{+}$	4.1851	1.6970	0.0945*
INF (i.e. ACE)$^{-}$	-0.0017	-1.9342	0.0574*
INF (i.e. ACE)$^{+}$	-0.0022	-0.4628	0.6450
HCSD (i.e. SER(-1))$^{-}$	2.0847	2.9669	0.0083***
HCSD (i.e. SER(-1))$^{+}$	-0.0040	-0.0431	0.9660
INF (i.e. ACE(-1))$^{-}$	-0.0974	-2.4101	0.0269**
INF (i.e. ACE(-1))$^{+}$	-0.0364	-0.6924	0.4975
Short-Run Panel:			
D(LOGIDO(-1))	-0.3293	-1.3365	0.1980
HCSD (i.e. DSER)$^{-}$	2.3521	2.9551	0.0085***
HCSD (i.e. DSER)$^{+}$	1.6436	1.8014	0.0884*
INF (i.e. DACE)$^{-}$	-0.0737	-2.3269	0.0318**
INF (i.e. DACE)$^{+}$	0.1682	1.8782	0.0766*
HCSD (i.e. DSER(-1))$^{-}$	4.1851	1.6970	0.0945*

HCSD (i.e. DSER(-1))$^{+}$	-2.4629	-0.7826	0.4366
IND (i.e. DACE(-1))$^{-}$	3.0348	1.1243	0.2650
INF (i.e. DACE(-1))$^{+}$	-0.0017	-1.9342	0.0574*
GCF (1st Control var.)	-0.0181	-1.8915	0.0815*
FDI (2nd Control var.)	0.0054	0.2628	0.7957
C	1.3929	1.8418	0.0865*
ECM(-1)	-0.1861	-3.5891	0.0005***
R-squared	0.9144	F-statistic	18.3496
Adj. R-squared	0.8856	Prob.	0.0097
Durbin-Watson stat.	1.9833		

Source: Author's Estimations (2024) in line with Shin and Greenwood-Nimmo (2014), *Shin (2016).* ***Note:*** *(***), (**), and (*) indicate 1%, 5% and 10% levels of significance, respectively.*

Explanation of the Asymmetric results in ECCAS

It has been observed that the indicators of human capital skills and infrastructure revealed asymmetric effects through a positive and negative shift in industrial output growth across the Economic Community of Central African States (ECCAS) bloc in SSA. A positive human capital skills and infrastructure shift increases industrial output growth in the ECCAS sub-region. In another direction, a negative human capital and infrastructure shift leads to increased industrial output growth in the ECCAS sub-region. This finding highlighted the asymmetric effect of human capital skills and infrastructure on industrial output growth in ECCAS. Based on the long-run results, a positive change in human capital skills through school enrolment rate-SER caused about 4.19 units increase in industrial output growth at a 10% significance level in the Economic Community of Central African States (ECCAS).

In contrast, a negative shift in human capital has an insignificant effect on industrial output growth in ECCAS. Likewise, a positive shift in infrastructure spread through access to energy has an insignificant effect on industrial output growth in the ECCAS bloc. In contrast, a negative change in infrastructure caused about 0.002 marginal units to drop in industrial output growth at a 10% significance level in ECCAS.

The lag magnitude of the asymmetric effect through human capital was more than that of infrastructure across the two regimes in ECCAS. That is, an adverse change in the lag of human capital skills through school enrolment rate-SER caused about 2.08 units rise in industrial output growth at a 1% level of significance, while a positive shift in the lag of human capital via SER has an insignificant impact on industrial output growth in ECCAS. Meanwhile, an adverse change in the infrastructure lag through access to energy caused about 0.097 units to fall in industrial output growth at a 5% significance level in ECCAS, while a positive shift in infrastructure has an insignificant impact on industrial output growth.

According to the short-run results, it was disclosed that human capital skills and infrastructure exhibited two regimes' effects on industrial output growth. For example, measuring human capital skills on industrial output showed a higher magnitude of asymmetric effects than infrastructure in the short run. That is, a positive rise in human capital skills caused about 1.64 units to rise in the magnitude of industrial output at a 10% significance level in the short run across ECCAS. Also, an adverse change in human capital skills caused about a 2.35 units magnitude increase in industrial output growth at a 1% significance level in the short run across ECCAS. Meanwhile, a negative fall in infrastructure brought about 0.07 marginal units fall in industrial output growth at a 5% significance level in the short-run, while a positive shift in infrastructure caused about 0.17 units increase in industrial output growth at a 10% significance level in the short-run. Meanwhile, the asymmetric effects of the short-run lag variables were marginal, as a negative shift in the previous year of human capital caused about 4.19 units to rise in the current year’s industrial output growth in ECCAS.

Meanwhile, a positive change in infrastructure caused a 0.001 unit fall in industrial output in ECCAS. The control factors through gross capital formation disclosed some levels of magnitude impact on industrial output growth. A unit rise in gross capital formation exogenously caused about 0.02 units to fall in industrial output growth at a 10% significance level across ECCAS. Control factors such as foreign direct investment exogenously disclosed an insignificant impact on industrial output growth in ECCAS.

Table 6.13: **Long-run and Short-Run Asymmetry Results**

Sub-Region	Wald Test	F-statistic	P-value	Decision (Inferences)
ECCAS	W_{LR_un}	13.608***	0.0035	Asymmetric
	W_{SR_un}	4.535**	0.0046	Asymmetric

Note: *WLR_un denotes the long-run asymmetric estimation; WSR_un captures the short-run asymmetric estimation; ***, **and * signifies significance at 1%, 5% and 10% level.*

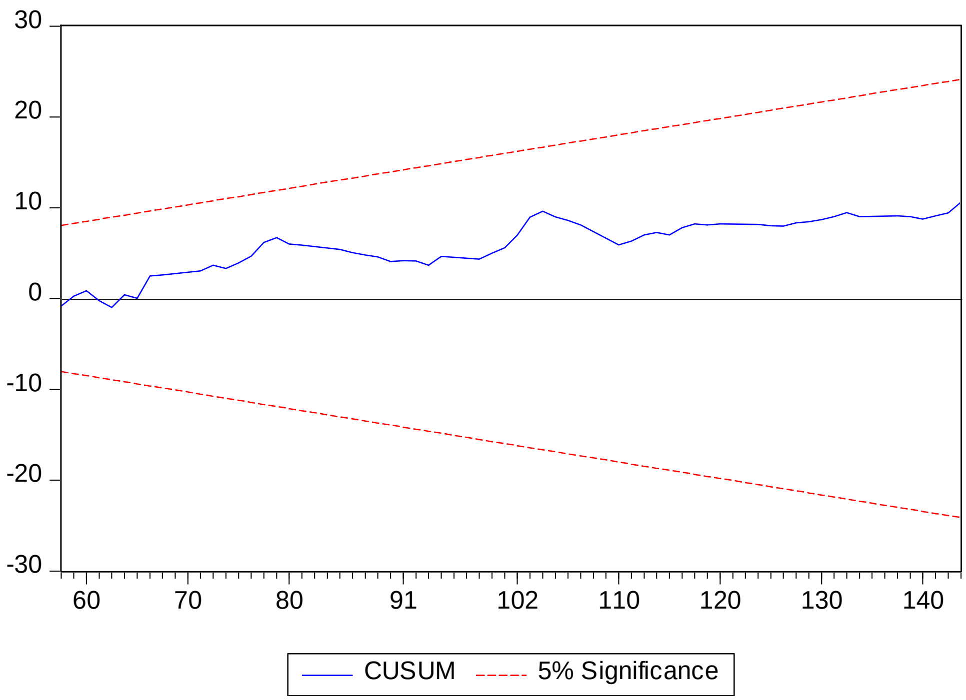


Figure 6.6: CUSUM Test for ECCAS

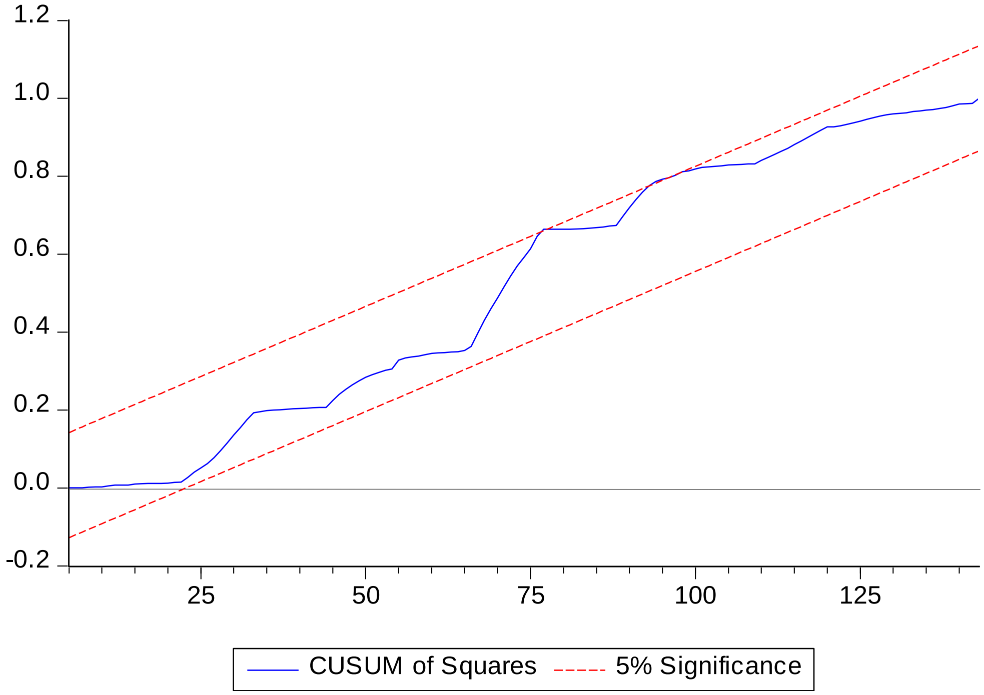


Figure 6.7: CUSUM Square Test for ECCAS

Table 6.14: ***Padroni's Panel Cointegrating reports for ECCAS***

within-dimension	Statistic	Prob.	Between-dimension	Statistic	Prob.
rho	-1.710646	0.0446**	G-rho	-1.747526	0.0928
PP	-7.670261	0.0000***	G-PP	-8.999385	0.0000***
ADF	-5.631799	0.0000***	G-ADF	-6.690856	0.0000***

Source: *Author's Computation 2024.* ***Note:*** *The long-run cointegration estimation was denoted by symbols ***, **and *, which signifies significance levels at 1%, 5%, and 10%. Included observations: 63, Cross-sections included: 9. Null Hypothesis: No cointegration.*

Generally, the NARDL model for the ECCAS sub-region exhibited both long-run and short-run asymmetric effects of human capital skills and infrastructure on industrial output growth. Interestingly, the Error Correction Model (ECM) coefficient disclosed a high speed of adjustment between the short-run and the long-run models at 18% at a 1% significant level. The specified models react quickly to possible shocks at the equilibrium point. Similarly, the F-statistic showed that the ECCAS NARDL model was statistically significant in predicting the asymmetric effect of the key variables. The R-square at 0.91437 showed that the independent variables explained the 91% variation in the dependent variable. The indicators of human capital skills and infrastructure explained 91% variation in industrial output growth in ECCAS. Also, the Durbin-Watson (DW) coefficient of about 1.98, approximately 2, indicated an absence of positive and negative autocorrelation in the overall model.

The diagnostics results further validated the empirical findings that disclosed the asymmetric effect of human capital skills and infrastructure on industrial output growth in ECCAS. Based on the Wald statistic outcomes, the null hypothesis of symmetric effect was rejected for both long-run and short-run. The Wald coefficients established the presence of a valid asymmetric effect of human capital skills and infrastructure on industrial output growth in ECCAS. The stability test through the CUSUM and CUSUM-Squares validated that the models specified were stable over time.

The cointegrating statistic disclosed different levels of cointegration across different estimating inferences, as suggested by Padroni. Notably, the null hypothesis of no cointegration among the panel dataset for the NARDL model can be strongly rejected. This is because two inference tools reveal some levels of cointegration within and between dimensions. For example, Philip-Peron (PP) and Augmented Decay-Fuller statistics demonstrated some levels of cointegration at 1% and 5% significant levels across the two cross-sections. The next step is to analyze the asymmetric effect of human capital skills and infrastructure regarding industrial output growth across ECOWAS sub-region.

Table 6.15: **Harmonized Panel NARDL Results across ECOWAS**

Panel Regressors	**Co-efficient**	**T-statistics**	**P-value**
Dep. Variable LogIdo			
Long-Run Panel			
(LOGIDO(-1))	-0.0153	-2.1786	0.0586**
HCSD (i.e. SER)$^{-}$	3.1572	1.0566	0.2927
HCSD (i.e. SER)$^{+}$	1.7287	3.8206	0.0002***
INF (i.e. ACE)$^{-}$	0.0262	0.8464	0.3990
INF (i.e. ACE)$^{+}$	-0.8031	-7.8699	0.0000***
HCSD (i.e. SER(-1))$^{-}$	-1.1909	-3.0177	0.0112***

HCSD (i.e. SER(-1))$^{+}$	-0.050929	-2.3456	0.0304**
INF (i.e. ACE(-1))$^{-}$	0.0115	0.1077	0.9144
INF (i.e. ACE(-1))$^{+}$	-0.021369	-1.9332	0.0736*
Short-Run Panel:			
D(LOGIDO(-1))	0.1089	1.0645	0.2888
HCSD (i.e. DSER)$^{-}$	0.301174	1.8642	0.0921*
HCSD (i.e. DSER)$^{+}$	-0.3596	-0.5409	0.5897
INF (i.e. DACE)$^{-}$	-0.0110	-3.9147	0.0089***
INF (i.e. DACE)$^{+}$	0.0868	2.7826	0.0300**
GCF (1st Control var.)	-0.0002	-0.3017	0.7635
FDI (2nd Control var.)	0.0204	2.3460	0.0331**
C	0.0223	0.2217	0.8250
ECM(-1)	-0.1109	-0.3786	0.0062***
R-squared	0.8329	F-statistic	16.309
Adj. R-squared	0.8219	Prob.	0.0000
Durbin-Watson stat.	2.1144		

Source: Author's Estimations (2024) in line with Shin and Greenwood-Nimmo (2014), *Shin (2016)*
Note: *(***), (**), and (*) indicate 1%, 5% and 10% levels of significance, respectively.*

Explanation of the Asymmetric results in ECOWAS

It has been observed that the indicators of human capital skills and infrastructure revealed asymmetric effects through a positive and negative shift in industrial output growth across the Economic Community of West African States (ECOWAS) bloc in SSA. A positive human capital skills and infrastructure shift led to increased industrial output growth in the ECOWAS sub-region. In another way, a negative shift in human capital and infrastructure estimates leads to increased industrial output growth in the ECOWAS sub-region. This finding stressed the asymmetric effect of human capital skills and infrastructure on industrial output growth in ECOWAS. Notably, the lag effect of industrial output growth negatively and significantly influences industrial output growth across the Economic Communities of West African States. According to the long-run NARDL results, a positive change in human capital skills through school enrolment rate-SER caused about 1.73 units increase in industrial output growth at 1% level of significance in the Economic Community of West African States economic (ECOWAS) bloc in SSA.

In contrast, a negative shift in human capital has an insignificant effect on ECOWAS's industrial output growth. However, a positive change in infrastructure caused about 0.80 units to rise in industrial output growth at a 1% significance level in the ECOWAS sub-region. A negative shift in infrastructure spread through access to energy has an insignificant effect on industrial output growth in the ECOWAS economic bloc.

The lag magnitude of the asymmetric effect through human capital proved to be more proactive than infrastructure across the two regimes in the ECOWAS sub-region. That is, a negative shift in the lag of human capital skills through school enrolment rate-SER caused about 1.19 units fall in industrial output growth at one per cent level of significance, while a positive shift in the lag of human capital via SER caused about 0.05 marginal fall in industrial output growth in ECOWAS region. Hence, the dual regimes' effect reacted differently to industrial output growth and showed an asymmetric relationship. Meanwhile, a positive shift in infrastructure has an insignificant impact on industrial output growth. Meanwhile, a negative shift in the infrastructure lag through access to energy caused about 0.02 units to fall in industrial output growth at a 10% significance level in ECOWAS.

According to the short-run results, infrastructure disclosed higher industrial output growth than human capital skills across the ECOWAS sub-region. It was also disclosed that human capital skills and infrastructure exhibited two regimes that affected industrial output growth. For example, a measure of human capital skills on industrial output showed a lesser asymmetric effect than infrastructure in the short run. That is, a positive rise in infrastructure caused about 2.78 units to rise in the magnitude of industrial output at a 5% significance level in the short run across the ECOWAS sub-region. Also, an adverse change in infrastructure caused a 3.91 unit magnitude fall in industrial output growth at a 1% significance level in the short run across ECOWAS. Meanwhile, a negative fall in human capital skills brought about 1.86 units to fall in industrial output growth at a 10% level of significance in the short run, while a positive shift in infrastructure had an insignificant influence on industrial output growth at a 10% level of significance in the short run.

Meanwhile, the asymmetric effects of the long-run lag variables were marginal, as a negative shift in the previous year of industrial output caused about 0.05 units to fall in the current year's industrial output growth in ECOWAS. The control factors through gross capital formation disclosed some levels of magnitude impact on industrial output growth. A unit rise in foreign direct investment exogenously caused about 0.02 units to fall in industrial output growth at a 10% significance level across ECOWAS. Control factors such as gross capital formation exogenously disclosed an insignificant impact on industrial output growth in ECOWAS.

Table 6.16: **Long-run and Short-Run Asymmetry Results**

Sub-Region	Wald Test	F-statistic	P-value	Decision (Inferences)
ECOWAS	W_{LR_un}	11.424**	0.0176	Asymmetric
	W_{SR_un}	2.324*	0.0711	Asymmetric

Note: *WLR_un denotes the long-run asymmetric estimation; WSR_un captures the short-run asymmetric estimation; ***, **and * signifies significance at 1%, 5% and 10% level.*

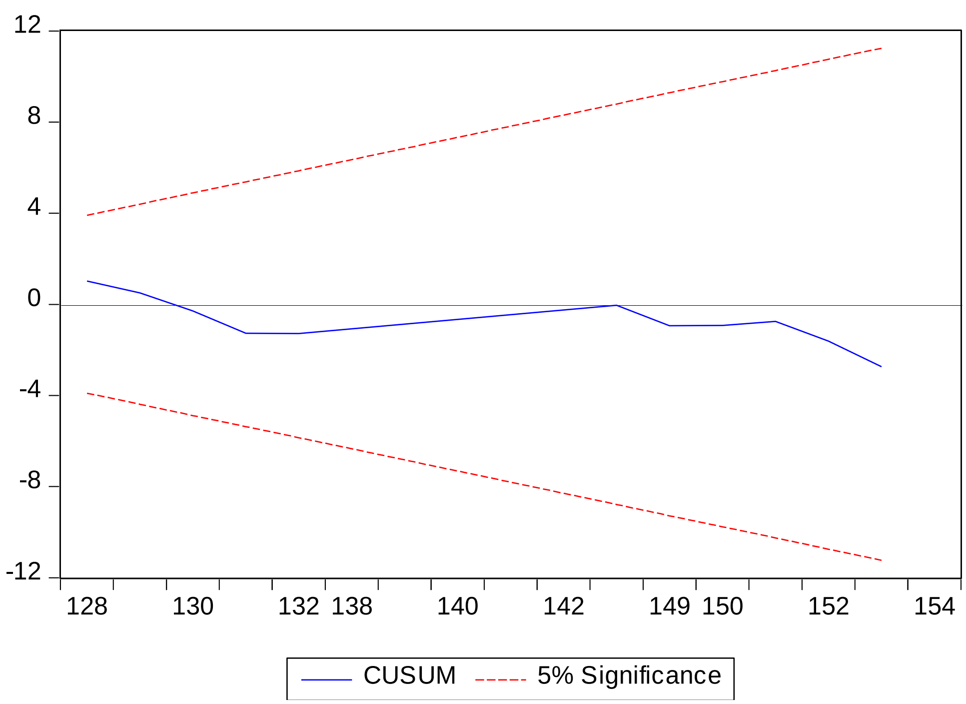


Figure 6.8: CUSUM Test for ECOWAS

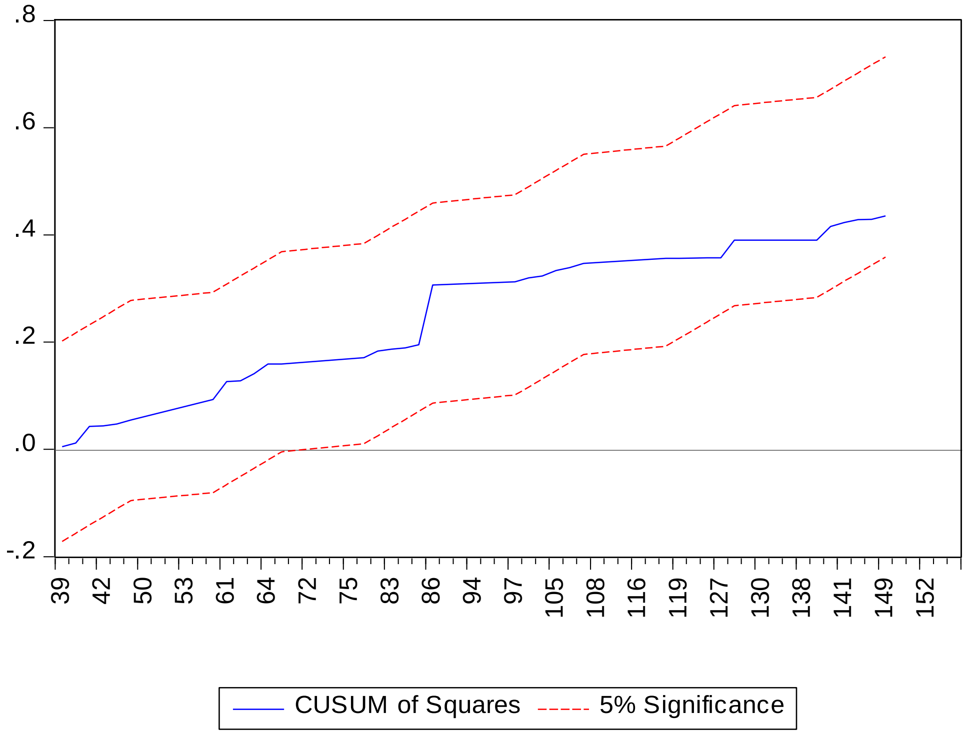


Figure 6.9: CUSUM SQUARE Test for ECOWAS

Table 6.17: ***Padroni's Panel Cointegrating reports for ECOWAS***

within-dimension	Statistic	Prob.	Between-dimension	Statistic	Prob.
rho	1.439257	0.0845	G-rho	2.992699	0.9986
PP	-1.710646	0.0446	G-PP	-1.963007	0.0503
ADF	-3.403470	0.0003	G-ADF	-3.902392	0.0000

Source: *Author's Computation (2024).* ***Note:*** *The long-run cointegration estimation was denoted by symbols ***, **and *, which signifies significance levels at 1%, 5%, and 10%. Included observations: 154, Cross-sections included: 14. Null Hypothesis: No cointegration.*

Generally, the NARDL model for the ECOWAS sub-region exhibited both long-run and short-run asymmetric effects of human capital skills and infrastructure on industrial output growth. Interestingly, the Error Correction Model (ECM) coefficient disclosed a high speed of adjustment between the short-run and the long-run models at 11% at a 1% significant level. The specified models react quickly to possible shocks at the equilibrium point. Similarly, the F-statistic showed that the ECCAS NARDL model was statistically significant in predicting the asymmetric effect of the key variables. The R-square at 0.8329 showed that the independent variables explained the

83% variation in the dependent variable. The indicators of human capital skills and infrastructure explained 91% variation in industrial output growth in ECOWAS. Also, the Durbin-Watson (DW) coefficient of about 2.11, approximately 2, indicated the absence of positive and negative autocorrelation in the overall model.

The diagnostics result further validated the empirical findings that disclosed the asymmetric effect of human capital skills and infrastructure on industrial output growth in ECOWAS. Based on the Wald statistic outcomes, the null hypothesis of symmetric effect was rejected for both long-run and short-run. The Wald coefficients established the presence of a valid asymmetric effect of human capital skills and infrastructure on industrial output growth in ECOWAS. The stability test through the CUSUM and CUSUM-Squares validated that the models specified were stable over time.

The cointegrating statistic disclosed different levels of cointegration across different estimating inferences. Notably, the null hypothesis of no cointegration among the panel dataset for the NARDL model can be strongly rejected. This is because two inference tools reveal some levels of cointegration within and between dimensions. For example, Philip-Peron (PP) and Augmented Decay-Fuller statistics demonstrated levels of cointegration at 1% and 5% significant levels across the two cross-sections. The next step is to examine the asymmetric effect across SADC.

Table 6.18: **Harmonized Panel NARDL Results across SADC**

Panel Regressors	**Co-efficient**	**T-statistics**	**P-value**
Dep. Variable LogIdo			
Long-Run Panel			
(LOGIDO(-1))	-0.0153	-1.9786	0.0586*
HCSD (i.e. SER)$^{-}$	0.4250	4.7716	0.0000***
HCSD (i.e. SER)$^{+}$	0.0661	1.5458	0.1274
INF (i.e. ACE)$^{-}$	0.0105	2.3684	0.0211**
INF (i.e. ACE)$^{+}$	-0.0039	-7.7603	0.0000***
HCSD (i.e. SER(-1))$^{-}$	-1.1909	-2.0177	0.0112***
HCSD (i.e. SER(-1))$^{+}$	-0.0509	-2.4758	0.0349**

INF (i.e. ACE(-1))$^{-}$	0.4251	1.5458	0.1274
INF (i.e. ACE(-1))$^{+}$	0.0661	4.7716	0.0000***
Short-Run Panel:			
D(LOGIDO(-1))	0.1089	1.0645	0.2896
HCSD (i.e. DSER)$^{-}$	0.3012	3.9624	0.0052***
HCSD (i.e. DSER)$^{+}$	-0.3596	-3.5409	0.0097***
INF (i.e. DACE)$^{-}$	-0.0338	-1.691025	0.0965*
INF (i.e. DACE)$^{+}$	0.0799	2.778598	0.0379**
GCF (1st Control var.)	-0.0003	-0.5236	0.6017
FDI (2nd Control var.)	0.030399	2.3409	0.0359**
C	3.1329	35.0005	0.0000***
ECM(-1)	-0.1760	-3.2365	0.0135**
R-squared	0.840561	F-statistic	18.3496
Adj. R-squared	0.8001	Prob.	0.0000
Durbin-Watson stat.	2.0307		

Source: Author's Estimations (2024) in line with Shin and Greenwood-Nimmo (2014), *Shin (2016)*
Note: *(***), (**), and (*) indicate 1%, 5% and 10% levels of significance, respectively.*

Explanation of the results for SADC

Evidence from the NARDL empirical analysis showed that indicators of human capital skills and infrastructure asymmetrically influence industrial output growth across the South African Development Community economic bloc (SADC) bloc in SSA. That is, positive human capital skills and infrastructure shift has led to increase in industrial output growth across the SADC sub-region. In another way, a negative shift in human capital and infrastructure indicators leads to decreased industrial output growth in the SADC sub-region. This finding stressed the asymmetric effect of human capital skills and infrastructure on industrial output growth in the SADC economic bloc.

Notably, the lag effect of industrial output growth negatively and significantly influences current industrial output growth across the SADC region. According to the long-run NARDL results, an adverse change in human capital skills through school enrolment rate-SER caused about 0.43 units increase in industrial output growth at a 1% level of significance in the South African Development Community economic bloc (SADC) in SSA. In contrast, a positive shift in human capital has an insignificant effect on SADC's industrial output growth. However, a positive change in infrastructure caused about 0.004 units to fall in industrial output growth at a 1% significant level in the SADC sub-region. Meanwhile, a negative shift in infrastructure spread through access to energy caused about 0.011 units of increase in industrial output growth at a 5% significance level in SADC.

The lag magnitude of the asymmetric effect through human capital proved to be more proactive than infrastructure across the two regimes in the SADC sub-region. That is, a negative shift in the lag of human capital skills through school enrolment rate-SER caused about 1.191 units to fall in industrial output growth at a one per cent level of significance, while a positive shift in the lag of human capital via SER caused about 0.051 marginal falls in industrial output growth in SADC region. Hence, the dual regimes' effect reacted differently to industrial output growth and showed an asymmetric relationship. Meanwhile, a positive infrastructure shift through energy access caused about 0.067 units of rise in industrial output growth at a 1% significance level across SADC. However, a negative shift in infrastructure lag has an insignificant impact on SADC's industrial output.

According to the short-run results, human capital skills disclosed higher industrial output growth than infrastructure across the SADC sub-region. It was also disclosed that human capital skills and infrastructure exhibited two regimes that affected industrial output growth in the short run. A measure of human capital skills on industrial output showed a higher magnitude of asymmetric effects than infrastructure in the short run. This means that a positive rise in infrastructure caused about 0.078 units to rise in the magnitude of industrial output at 5% significance in the short run across the SADC sub-region. Also, an adverse change in infrastructure caused about 0.034 units of magnitude to fall in industrial output growth at a 10% significance level in the short run across SADC. Meanwhile, a negative fall in human capital skills brought about a 0.11 units rise in industrial output growth at 1% level of significance in the short run, while a positive shift in human capital skills brought about a 0.36 units fall in industrial output growth at 1% level of significant in the short-run.

Meanwhile, the asymmetric effects of the long-run lag variables were less effective, as the previous year's industrial output disclosed an insignificant impact on the current year's industrial output growth in the short run across SADC. The control factors through gross capital formation disclosed some levels of magnitude impact on industrial output growth. A unit rise in foreign direct investment exogenously caused about 0.030 units to rise in industrial output growth at a 5% significance level across SADC. Control factors such as gross capital formation exogenously disclosed in

Consequently, the NARDL model for the SADC sub-region exhibited both long-run and short-run asymmetric effects of human capital skills and infrastructure on industrial output growth. Interestingly, the Error Correction Model (ECM) coefficient disclosed a high speed of adjustment between the short-run and the long-run models at -0.176055 (of about 17%) at a 1% significant level. The specified models react quickly to possible shocks at the equilibrium point. Similarly, the F-statistic showed that the SADC NARDL model was statistically significant in predicting the asymmetric effect of the key variables. The R-square at 0.840561 showed that the independent variables explained the 84% variation in the dependent variable. The indicators of human capital skills and infrastructure explained 84% variation in industrial output growth in SADC. Also, the Durbin-Watson (DW) coefficient of about 2.03, approximately 2, indicated an absence of positive and negative autocorrelation in the overall model.

Table 6.19: **Long-run and Short-Run Asymmetry Results**

Sub-Region	Wald Test	F-statistic	P-value	Decision (Inferences)
SADC	W_{LR_un}	21.3096***	0.0000	Asymmetric
	W_{SR_un}	3.324**	0.0610	Asymmetric

Note: *WLR_un denotes the long-run asymmetric estimation; WSR_un captures the short-run asymmetric estimation; ***, **and * signifies significance at 1%, 5% and 10% level.*

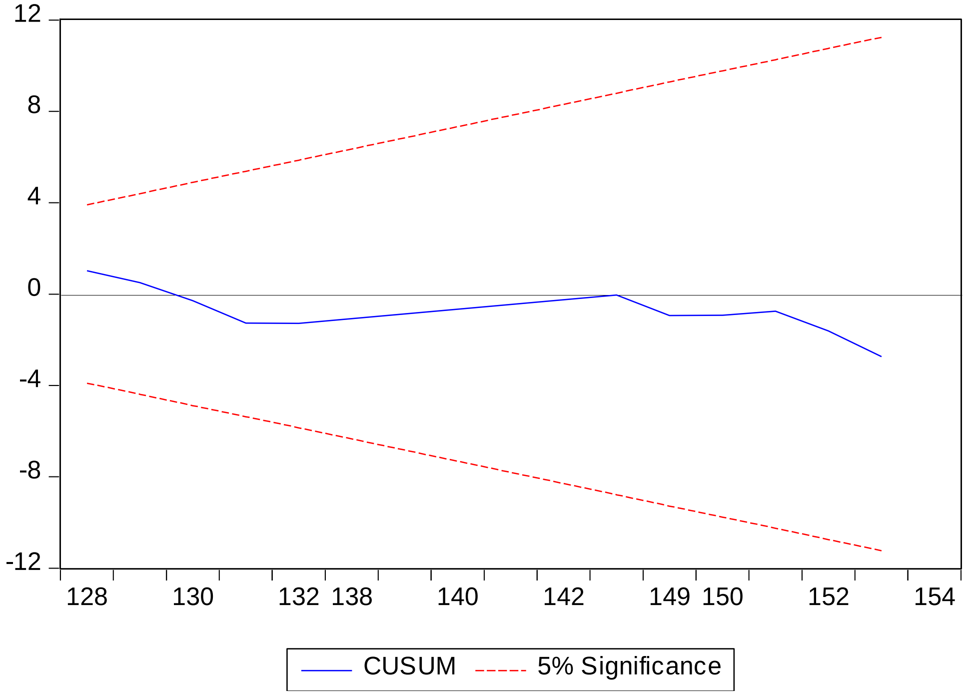


Figure 6.10: CUSUM Test for SADC

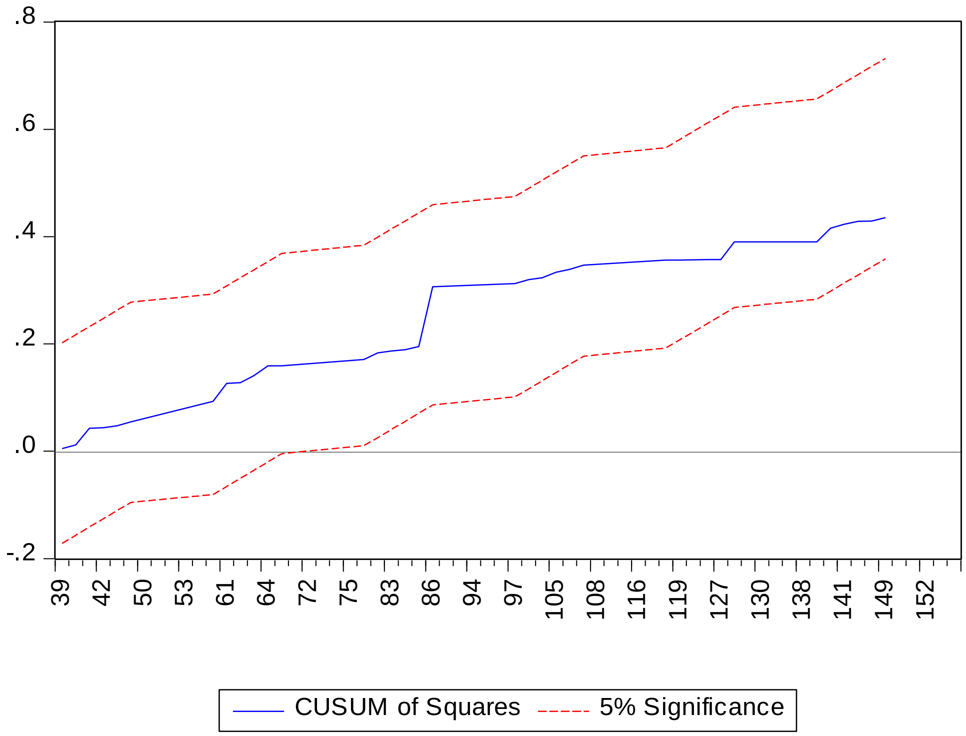


Figure 6.11: CUSUM Square Test for SADC

Table 6.20: ***Padroni's Panel Cointegrating reports for SADC***

within-dimension	Statistic	Prob.	Between-dimension	Statistic	Prob.
rho	-1.375731	0.0845	G-rho	0.009152	0.5037
PP	-2.575576	0.0050	G-PP	-2.258940	0.0119
ADF	-1.701191	0.0445	G-ADF	-1.677186	0.0900

Source: *Author's Computation (2024).* ***Note:*** *the long-run cointegration estimation was denoted by symbols ***, **and *, which signifies significance levels at 1%, 5% and 10%.* Included observations: 415, Cross-sections included: 13. Null Hypothesis: No cointegration.

The diagnostics results further validated the empirical findings disclosed through the asymmetric effect of human capital skills and infrastructure on industrial output growth in SADC. Based on the Wald statistic outcomes, the null hypothesis of symmetric effect was rejected for both long-run and short-run. The Wald coefficients established a valid asymmetric effect of human capital skills and infrastructure on industrial output growth in SADC. The stability test through the CUSUM and CUSUM-Squares validated that the models specified were stable over time.

The cointegrating statistic is disclosed at different levels of cointegration across different estimating inferences. Notably, the null hypothesis of no cointegration among the panel dataset for the NARDL model can be firmly rejected. This is because two of the inference tools revealed some levels of cointegration within and between dimensions. For example, Philip-Peron (PP) and Augmented Decay-Fuller statistics demonstrated some levels of cointegration at 1% and 5% significant levels across the two cross-sections. The next step is to discuss the implications of the results across the SSA sub-region.

6.8 DISCUSSION OF THE FINDINGS

The general outcomes from the individual sub-regional regimes' effects disclosed that each sub-region portrayed its own specific dual effects from the explanatory variables to the explained variable. For example, the magnitude of dual effects in SADC was higher than in other sub-regional economic blocs. Meanwhile, ECCAS ECOWAS and EAC trailed SADC in the following order: Notably, human capital skills and infrastructure indicators showed higher dual effects than asymmetric effects in ECCAS ECOWAS and EAC. Based on these outcomes, individual sub-regions must concentrate on the indicators with more comparative advantage for sustainable industrial sector growth across economic blocs in SSA. This is because most of the significant coefficients exhibited marginal dual effects on industrial output across the sub-regions. It is also worth noting that the panel dataset from SADC under the FE-LSDV models in Chapter 5 continued to fare better than others ECOWAS EAC using asymmetric models.

Regarding comparative advantage, the findings disclosed that SADC's human capital skills proactively influence industrial output growth, while the ECOWAS sub-region trailed behind SADC despite having the highest number of human capital skills, which is an implication for this study. The literary implication is that skills acquisition was important in industrial output growth. Similarly, the infrastructure spread asymmetric effects across the sub-regions proved marginal on industrial output growth.

6.9 CONCLUSION AND CONTRIBUTIONS

This study developed a unique perspective toward improving industrial output growth across sub-Saharan Africa's four sub-regional economic groups by adopting threshold and nonlinear Autoregressive Distributed Lags using panel data analysis. This unique approach was adopted because it has been challenging to address slow industrial output in SSA. None of the previous studies investigated the effects of dual regimes across SADC ECCAS ECOWAS and EAC sub-regional blocs in SSA effects. Inferences from the empirical results showed that poor productive skills and poor infrastructural spread across the sub-regional group predicate slow industrial output growth in SSA. For example, the ECCAS and ECOWAS communities performed better than the ECA and SADC communities regarding average means of human capital skills and infrastructure spread in SSA. Therefore, there is a need for individual countries and sub-regions to follow the path of East Asia countries and regions regarding prioritizing physical and human capital development to expedite massive industrial sector growth in SSA. Different governance/public fiscal styles predicated industrial productivity growth via poor productive labour skills and poor infrastructural spread across the sub-regions. It is pertinent for authorities in each sub-region to develop home-based policies potentially driven by the least comparative disadvantage regarding technology transfer and annexing available human capital and physical resources to expedite industrial sector growth.

Nonetheless, the study is not free from the problem of data accessibility. A few countries in SSA lack data on some of our key variables, and they were dropped. Apart from this unavoidable challenge, forty sub-SSA countries were investigated in the study, which was very large enough to predict industrial output performance via threshold and asymmetric effects of human capital skill development and infrastructural-techs development on industrial output growth across EAC ECCAS ECOWAS SADC.

6.10 CONTRIBUTIONS OF CHAPTER SIX

The previous debate illustrates that there is no study on the threshold and asymmetric effects of HCSD and INF on IDO across SSA. While several studies have focused on this issue in developed countries, few have been shown in the SSA region, and those that existed were from different focuses confined to specific countries.

Also, the study narrowed down the broad concept of human capital to human capital skill development to account for labour effort's contribution to industrial output growth. It broke down the broad concept of infrastructure to productive physical infrastructure that directly influences industrial output growth across the sub-regional economic blocs in SSA. Most previous studies emphasised the direct effect or symmetry of the key explanatory variables, while this study went the extra mile to disclose two regimes' effects at sub-regional levels across the sub-Saharan states. A study in this direction would fill notable gaps in the literature. Particularly, findings from previous studies were often mobbed up using SSA as a whole single entity without paying due attention to the sub-regional specific dual effects of human capital skills and infrastructure on industrial output growth. This study was mindful of individual country and sub-economic group-specific asymmetric effects. Therefore, this study path is scanty in the body of empirical literature as the study adopts a panel GMM and NARDL methods to establish dual effects of threshold and asymmetry of HCSD and INF in SSA. Post-estimation techniques such as autocorrelation, CUSUM, and Wald statistic tests were used. Notably, these diagnostics tests were carried out to validate our overall findings. Multiple empirical techniques were adopted in the study to corroborate and validate our empirical results and avoid the inherent problems in one method scenario.

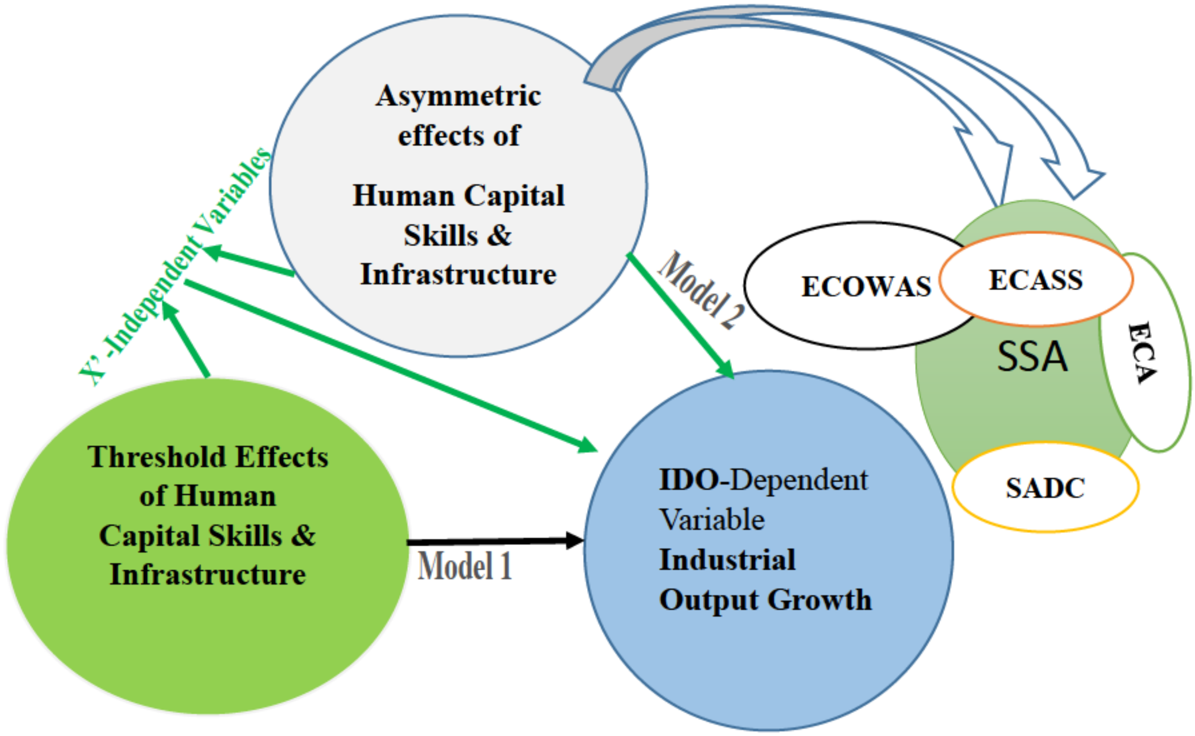


Figure 6.12: Recap on Schematic View of the Gaps and Contributions to the Literature

Source: Researcher, (2024).

The schematic Figure in 6.10 demonstrates the vacuums this study has filled in the literature by investigating sub-regional asymmetric effects of human capital skills and infrastructure on industrial output growth. This is to provide proactive sub-regional policy support to address individual sub-regional bloc productive challenges. Previous policy supports from early studies mainly had failed to address contemporaries' productive challenges facing the four sub-region economic blocs- ECA, ECCAS, ECOWAS, and SADC across SSA, due to their inability to show individual sub-regional specifics regarding human capital skills composition and infrastructural spread that can expedite industrial sector growth. The study incorporated five pillars of model building in economics to answer the magnitude of threshold and asymmetric roles of human capital skills and infrastructure across SSA's sub-regional economic blocs.

CHAPTER SEVEN

SUMMARY, CONCLUSION AND RECOMMENDATIONS

7.1 SUMMARY

Firstly, the study investigated the determinants of industrial output growth in sub-Saharan countries through trend analysis and two-step system GMM techniques. It was established that certain indicators of human capital skills and infrastructure, such as SER AYS LER LIR LPR LBF HOC FDI GCF ACE ACT ICT and AWP, primarily influence industrial output growth in SSA. Secondly, based on the first objective's outcome, the study examined the comparative effect of human capital skills and infrastructure development on industrial sector growth across the sub-regional economic blocs in SSA. This was premised on the fact that productive human capital skills and infrastructural spread in SSA proved to be the least prevalent among its contemporaries across the globe, hence negatively impacting industrial sector growth. Thirdly, the threshold and asymmetric effect of human capital skills and infrastructure were examined across SSA's four sub-regional economic blocs. The study disclosed individual sub-regional specifics and their dual effects of human capital skills and infrastructure on industrial output growth. This study contributed to the mainstream economic literature by defining the threshold trajectory for improved industrial output growth in SSA. This study established the effects of the two regimes on human capital skills and infrastructure across the individual sub-regional economic blocs in SSA. Hence, disclosing factors (indicators) responsible for slow industrial output growth and offering the necessary answers.

The general importance of enhancing human capital and infrastructure in promoting industrial output growth has been addressed by Kuckuck (2012), Eigbiremolen and Anaduaka (2014), Kutu and Ngalawa (2016), Iqbal et al (2018), Akinola and Mbonigaba (2019), Jones (2019), Fawehinmi, Omolade, and Keji (2019), Keji (2020), Akinlo (2020) and Du et al. (2022), among others. These studies submitted that a policy framework that pursues the improvement of human capital and infrastructure would promote sustainable industrial output growth in small open economies like SSA countries. However, the sustainability of such a policy framework in stabilizing industrial output growth rests on the effectiveness of the transmission mechanism that is often preceded by policy inconsistent and poor implementation, vulnerability, structure and interaction of the determining factors. In theory, it is believed that an increase in determining measures for human capital skills alongside determining measures for infrastructure promotes industrial output growth (Rebelo, 1991; Mankiw, 1995). However, the performance of these determining factors is susceptible to being fully untapped and underutilised, particularly in productive growth. Consequently, the first objective was to address the factors determining industrial output growth in SSA, as supported by the theoretical intuition of improving measures for human capital skills and infrastructure policy transmission mechanism framework.

The factors that determine industrial output growth in SSA countries were identified through panel data estimation through the modelling of endogenous output growth by expressing IDO as a function of SER-school enrolment rate, AYS-average year of schooling, LIR-literacy rate, LPR-labour participation rate, LBF-labour force, LER-life expectancy rate, ACE-access to energy, ACT-access to transportation network, ICT- information technology, AWP-access to water, HOC-house consumption, FDI-foreign direct investment and GCF-gross capital formation. The study adopted a two-step system generalised method of moment conditions (Sys-GMM) among 40 SSA countries for short – and long-run analysis.

The results revealed that school enrolment rate, average year of schooling, information technology and access to transportation networks have a negative and significant link with industrial output growth among the sub-region countries under review, contrary to the a priori expectation and pertinent economic theory. The life expectancy rate, household consumption, and access to water exhibited an insignificant influence on industrial output growth. Meanwhile, determining factors supporting the literature were labour force, labour participation rate, literacy rate, access to energy, gross capital formation and foreign direct investment, which positively and significantly influence industrial output growth in the short and long run. This outcome supported the a priori expectation as positive interactions disclosed dynamic effects under the augmented endogenous theory. It is in support of empirical findings from Romer (1988), Rebelo (1991), Mankiw (1995), Kuckuck (2012) and Du et al. (2022). The outcomes imply that the performance of determining factors of industrial output growth in SSA is low, and this could be addressed through policies that improve school enrollment rates, the average year of schooling, information technology, and access to transportation networks. Post-estimation tests were conducted to validate the empirical results from sys-GMM.

Regarding the second objective, the study assessed the comparative effect of human capital skills development and infrastructure development on industrial output growth across sub-regional blocs in SSA. The relative productive skills and infrastructure spread level were compared across SSA sub-regions. Higher human capital skills and improved infrastructural spread are expected to promote industrial output growth, but evidence suggests otherwise in the case of SSA. The study revealed what might be responsible for this contraction and proffered the needed answers. Related studies such as Bokana and Akinola (2017), Edeme et al. (2020), Akinlo (2020), Keji (2021), Du et al. (2022) and Hoja, Yu and Mohamed (2022), among others, partly duel much on the link between human capital and output growth without indebt study on the relevant, productive element of infrastructure and human capital such as a skill that could directly contribute to industrial output growth. Previous studies are susceptible to underutilising human capital skills with poor complementarity roles in infrastructure development, especially when nations are clamouring for a knowledge-based economy primarily supported by high-tech infrastructure spread. In the case of filling the notable gaps, the second objective model rested on the link between the augmented endogenous output function and the technical progress function with the necessary clews from Kutu and Ngalawa (2016), Hongzhong, Hossain, and Sultanuzzaman (2018), Nkemgha Nchofoung, and Sundjo (2022), Bouattour, Kalai and Helali (2024) and Keji, Akinola and Mbonigaba (2024). The output value Y was disaggregated as a function of HCS and INF with notable clews from related works in Mendes et al. (2011), Kutu and Ngalawa (2016), Orji, Worika and Umofia (2017), Ndombi Ondze (2021), Goulielmos, (2021), Amoah and Jehu-Appiah (2022), Huang, Zeng, Wang, and Zhang (2022), Jiang (2022) and Keji, Akinola and Mbonigaba (2024).
Under this section, the study adopted both the static panel models (sub-sample analysis, fixed effects and least square dummy variable (LSDV)) and dynamic panel models (systemic generalised method of moments (Sys-GMM)), which cut across the four sub-regional economic blocs (i.e. EAC ECCAS ECOWAS and SADC) in SSA.

Consequently, the results showed mixed comparative effects of human capital skills and infrastructure on industrial output growth. Human capital skills proxy as school enrolment, labour participation rate, literacy rate, and infrastructure proxy as access to energy, transport, and information technology disclosed negative and positive coefficients in both static and dynamic estimation models. Indicators for the labour force changed from positive to negative effects while alternating between static and dynamic models that contradicted a priori expectations. Meanwhile, other indicators for HCS and INF eminently support the a priori expectation of human capital skills and technical progress theories. Validity tests such as

IDO as a function of SER-school enrolment rate, AYS-average year of schooling, LIR-literacy rate, LPR-labour participation rate, LBF-labour force, LER-life expectancy rate, ACE-access to energy, ACT-access to the transportation network, ICT- information technology, AWP-access to water, HOC-house consumption, FDI-foreign direct investment and GCF-gross capital formation. The study adopted a two-step system generalised method of moment conditions (Sys-GMM) among 40 SSA countries for short – and long-run analysis. Arellano-Bond of the two-step system GMM disclosed that the findings were free from serial autocorrelation. Similarly, the number of instruments is lesser than the number of groups. The Hansen/Sargan test statistic conventional rule of thumb posits that the null hypothesis of "the instruments as a group which are exogenous." Hence, the Hansen p-value is less than one, which indicates better Hansen statistics.

So, static and dynamic effects of human capital skills and infrastructure were examined to ascertain the current state of industrial output growth in EAC ECCAS, ECOWAS and SADC. This study addresses the concept of human capital skill and infrastructure, particularly as a direct input-output factor of production. Also, human capital and infrastructure spread effects were disaggregated along with their economic effects via short-run and long-run practicality to the industrial sector. Notwithstanding, most of the early studies arrived at some conclusions regarding policy framework effectiveness in stimulating output growth, but these studies could not draw policy suggestions based on the choice of estimates and sub-regional bloc case studies. This study covers these gaps by narrowing our research case study to sub-regional levels along the SSA region to proffer specific answers to individual sub-regional perennial problems of slow industrial growth. Therefore, this study suggested an effective home-grown policy framework for addressing sub-regional and peculiar challenges related to industrial growth, which was not common in previous studies.

The third specific objective in this study employed panel unit root test, correlation matrix, panel threshold regression analysis and harmonized nonlinear Autoregressive Distributed Lags (NARD) models to estimate the threshold and nonlinear effect of human capital skills and infrastructure on industrial output growth in SSA. The study disclosed certain thresholds for improving industrial output growth in SSA. Threshold targets were set across all the explanatory variables to show certain trajectory levels for output growth toward addressing inconsistent policy issues in the SSA sub-region. This was premised on low industrial output growth predicated upon poor human capital skill development and weak infrastructural spread across SSA. Findings from the study deduced that setting certain threshold targets would improve policy drafts for expanding industrial output in SSA. Also, the results from NARDL models disclosed dual regimes of effects of human capital skills and infrastructure on industrial output growth across EAC ECASS ECOWAS and SADC in SSA. Post-estimation tests were conducted using the CUSUM, CUSUM-SQAURE, and Wald statistic Test. Lastly, long-run checks through Padroni's Panel Cointegrating analysis were conducted.

Meanwhile, a few related studies on human capital and infrastructure, such as Stoichev (2014), Keng, Perepelkina, Perepelkinaa, and Morozovaa (2016), Aderogba and Adegboye (2019), Lin and Orazem (2017), Abdulqadir and Asongu (2021), Emily and Muyengwa (2021), Shahrivar et al. (2022), Harnani et al., (2022), Tortorelli et al. (2022) primarily focus on the symmetric nexus with less attention on the possible asymmetric (nonlinear) effect of human capital skills and infrastructure on industrial output growth across SSA. This study is unique because it provides a unique direction towards estimating dual regime effects and varied policy options for improved industrial output growth in the sub-region. Hence, this study provides a better understanding of nonlinear effects through threshold and NARDL estimating techniques.

In conclusion, this study first examined the factors determining industrial output growth in SSA. A necessary pre-estimation technique was carried out to achieve the first objective by identifying the determinants of industrial output growth through panel unit root and cross-section data estimations to accurately account for sources of industrial output growth pertinent to expanding production. This paved the way for indicators such as school enrolment-SER, average year of schooling-AYS, labour participation rate-LPR, labour force-LBF, household consumption, literacy rate LIR, life expectancy-LER, access to energy-ACE, access to transportation-ACT, access to water, information technology-ICT and foreign direct investment-FDI and gross capital formation-GCF as controlled factors. Interestingly, most of these indicators significantly influence industrial output growth in SSA through the disaggregated two-step GMM system approach. These variables were the true measures of human capital skills-HCS and infrastructure –INF.

It appeared from the first objective outcomes that industrial output growth was influenced by school enrolment, average year of schooling, labour participation rate, labour force, literacy rate, life expectancy rate, access to energy, access to transportation, access to water, information technology and foreign direct investment and gross capital formation (as controlled factors) were statistically significant. Also, the F-statistics results across the models showed that the models were statistically significant along with the probability values. Consequently, the study achieved the first objective by investigating the long-run determinants of industrial output growth in SSA through the two-step system GMM. The two steps of the dynamic GMM model were disaggregated into short-run and long-run effects to establish how components of human capital skills influence output growth. The evidence from GMM results disclosed that school enrolment rate (SER) and average year of schooling (AYS), Access to energy (ACE), and information techs (ICT) were negative and statistically significant in influencing industrial output growth. Also, literacy rate (LIR) and life expectancy rate (LER), gross capital formation (GCF) and foreign direct investment (FDI) were positive and statistically significant at a five per cent significance level to affect industrial output growth. The ability to communicate effectively, better labour life span, internationalization of knowledge via foreign direct investment and massive local investment through gross capital formation indicators were statistically significant.

Meanwhile, the labour participation rate and labour force did not follow apriori expectations. This implies poor skill possessed by labour human capital across the region. The long-run system GMM outcomes showed that variables for school enrolment as a source of the formal or conventional mean of knowledge acquisition were negative and statistically significant on industrial output growth. Also, the opportunity cost of skill acquisition proxy, as the average number of years of schooling, is statistically insignificant in the long run. The implication is that labour human capital skills could not adjust to a productive life in and out of school.

Regarding the second objective, the study employed trend analysis, sub-regional specifics correlation analysis, sub-sample analysis, Fixed-LSDV technique and confirmatory technique via two-step system GMM methods of analysis to address the specific comparative effects of human capital skills and infrastructure spread within the sub-regions. These methods were used to ascertain countries, sub-regional and regional specifics comparative effects on industrial sector growth. The significant difference between the fixed and random models was conducted, as disclosed through the Hausman test. In that regard, some of the explanatory variables in the random effect model were biased. Random effect outcomes disclosed the overall significance of biased estimates, unlike the fixed effect model, which was free from biased estimates.

Consequently, the study used the Fixed Effect Least Square Dummy Variables technique to disclose countries and sub-regional specific comparative effects. Also, based on the outcomes from the trend analysis, sub-sample analysis and fixed effect techniques, it was disclosed that human capital skill and infrastructure development have joint comparative effects on industrial sector growth in SSA, which makes this study unique. That is, each of the factor inputs portrayed diverse comparative effects across the sub-regions in SSA. For instance, human capital skill has more comparative effects on output growth in SADC than in ECOWAS; likewise, infrastructural spread in ECCAS and SADC have more significant effects than EAC and ECOWAS. The study further confirmed the inferences drawn from the FE-LSDV results by employing the dynamic short-run and long-run system GMM techniques. The dynamic system GMM estimation disclosed that the comparative effect of human capital skill and infrastructure development affects industrial output growth in SSA in the short and long run. The dynamic models disclosed how HCSD and INF jointly influence industrial output growth in SSA.

This study used a panel unit root test, correlation matrix, and threshold regression analysis to achieve the third specific objective. It harmonised nonlinear Autoregressive Distributed Lags models to estimate the threshold and nonlinear effect of human capital skills and infrastructure on industrial output growth in SSA. The study disclosed certain thresholds for improving industrial output growth in SSA. Threshold targets were set across all the explanatory variables to show certain levels of output growth for addressing inconsistent policy issues in SSA. This was premised on low industrial output growth, which is predicated upon poor human capital skill development and weak infrastructural spread across SSA. Findings from the study deduced that setting specific threshold targets would improve policy drafts for expanding industrial output in SSA. For example, governance policy issues like an increase in school enrolment rate as the source of formal skill acquisition for human capital skills development, the average year of schooling as the better opportunity cost of labour's skill attainment, improved vocational training centres and small and medium scale empowerment programs, among others productive skill programs would attract adequate attention. Also, massive public infrastructural investment, especially through energy, road, water, and information technology access, would enjoy a certain threshold target for rapid industrial output growth. Threshold outcomes were meant to smoothen the industrialisation drive of any country or region, particularly through a particular trajectory, which was disclosed in the study.

Consequently, the study disclosed stakeholders' trajectory towards improving industrial output growth in SSA. As illusionary theorists argued, this would eventually cut recklessness and wastage of fiscal outlays in public settings. Given this, the study believed that different styles of governance were being practised across the sub-regions in SSA. Therefore, there is a need for a specific threshold trajectory towards expanding industrial output growth in the sub-region.

Also, the asymmetric effect was disclosed across the four sub-Saharan regional blocs. This was premised on the need to embrace the opportunity cost of production in line with production advantages and disadvantages across individual sub-regions. The study revealed areas where sub-regions can invest in rapid industrial output growth. Evidence from the NARDL models showed that SADC sub-regions are better than other sub-regions like EAC ECCAS and ECOWAS in terms of human capital skills development for industrial output growth. This aligns with current realities as countries like South Africa, Botswana, etc., have better education systems than countries from other blocs. Notably, among the ECOWAS countries, particularly Nigeria, with her vast deposit of human capital, has a poor education system, as none of the country's universities was ranked among the top twenty in Africa compared to her counterpart from SADC. Interestingly, dual effect regimes adopted in the study attested to SSA's current low industrial output, especially across the sub-regional economic blocs.

Inferences were drawn from the four economic blocs to ascertain individual sub-regional specifics towards the domestication of policy draft. Based on the findings from the NARDL models, individual sub-regions would be able to address perennial challenges through better policy choices. The short-run and long-run of the asymmetric effect were elaborated across the sub-regional community to reveal the current state of industrial output in those blocs. Also, the study conducted a series of diagnostic and robust checks to establish the dual effect of human capital skills and infrastructure on industrial output growth across SADC, ECCAS, EAC and ECOWAS. Consequently, the study revealed that human capital skills and infrastructural techs have significant asymmetric effects on industrial sector growth in SSA via the short-run and long-run NARDL analysis methods.

In summary, across all the analysis methods through the first, second, and third objectives, pre- and post-estimation tests such as diagnostics tests were conducted for autocorrelations, over-identification of instruments, and Wald test to establish nonlinear relationships. Notably, the pre-estimation carried CSD across the first and second generation of unit root tests showed that our measurement variables were reliable and free from any form of breaks. Also, findings after our empirical investigations indicated that the number of instruments used in all the Sys-GMM estimations did not have any adverse effect on the estimators of the Sys-GMM and no auto-correlation was found at both the first and the second order without being automatically corrected. At some points, the first-order autocorrelation is corrected through the second-order autocorrelation, while at some points, there were no autocorrelations in both orders. Notably, the study corrected the limitations of F-LSDV and sub-sample regressions techniques via the two-step dynamic System GMM. The system GMM was adopted to address possible simultaneity, measurement error and endogeneity that might influence our findings, a major problem in panel data analysis. Hence, it is evident that this study has passed the overall diagnostics tests.

7.2 POLICY IMPLICATIONS

The study identified the factors determining industrial output growth in SSA through indicators such as SER AYS LER LIR LPR LBF HOC FDI GCF ACE ACT ICT and AWP in SSA's sub-regions. Consequently, certain variables, such as SER LPR LBF ACE ACT AWP, failed to exhibit the expected significant effects. This is an implication for the sub-regional industrial sector growth across SSA. This indicates a deficiency in SSA's effective educational policy and general policy drafts. In the meantime, the outcomes of this nature are timely, and they would possibly provide policy direction for SSA countries, as posited by Muwanguzi et al. (2018) in the case of Uganda's Vision 2040 and Mpofu and Nemashakwe (2023) towards Zimbabwean preparedness for the fourth industrial revolution.

Having discovered the problems confronting industrial output growth in SSA, the study sought to investigate the comparative effect of human capital skills and infrastructure on industrial output growth across four sub-regions in SSA. This was motivated to address industrial output growth challenges across sub-regional economic blocs in SSA. This was basically to revamp general industrial output growth in SSA.

Also, some of the salient facts emerging from the study showed that HCS and INF have time-path comparative influence through short-run and long-run on industrial output growth across the region. The implication is that human capital skills and infrastructure techs have a time-path impact on industrial output growth by catalyzing industrial output growth across sub-regions in SSA. Notably, the findings from this study are different from the previous studies, like Otalu and Keji (2015), Nchege, and Dorathy (2020), Akinlo (2020), Keji (2021; 2023), Du et al. (2022), Hoja, Yu and Mohamed (2022), Melikhaya (2022), Wegari et al., (2023) and Njenga (2024) but agreed to conclude that SSA's stakeholders had failed to expand output growth. Meanwhile, this study looks inwardly to show that slow industrial sector growth across SSA's countries and sub-regional blocs was mainly connected with poor knowledge development and a lack of high-tech infrastructure advancements. The evidence from this study showed that SSA is still lagging behind other regions of the world in terms of industrial sector growth. The implication is that the SSA nations do not have the requisite educated human capital and infrastructural spread required to sustain their industrial sector growth. Hence, the sub-region lacks a product or commodity identity, like its counterparts in East Asia, Europe, and America. That is, apart from the poorly processed agricultural goods, the SSA region does not have specialized modern goods it can be identified with as a major producer compared to other regions, such as East Asia, which can be identified with mobile phones and automobile techs. Even South Asia, which seems less competitive regarding product identities, strives well in Information Communication Technology (ICT) courtesy of India. Therefore, this study is a wake-up call for SSA to move along with its contemporaries.

The study has identified problems in the public sector that are confronting the industrial sector. The study sought to investigate the factors determining industrial output growth, the comparative effects of those factors on industrial output growth across sub-regional blocs and the threshold and asymmetric effect on industrial output growth across sub-regional economic blocs in SSA. Also, diverse means were drawn to compare the present state of industrial sector growth across other world regions. Evidence showed that SSA had a poor comparative effect to other regions in the trend analysis. The trend reports disclosed a structural deficit in the public sector regarding public allocation to human capital skill and infrastructural tech investment across sub-regions in SSA. Also, the trend analysis revealed a poor level of access to necessities of life that can catalyze industrial output growth compared to other regions of the world.

This result implies that countries across the sub-regional blocs do not have well-skilled human capital and adequate infrastructure to enhance their industrial output growth. This led us to another objective to seek the necessary way forward through the threshold and asymmetric effect of human capital and infrastructure development across EAC ECASS ECOWAS and SADC in SSA.

Consequently, the study discovered that countries in SSA had diverse and specific asymmetric effects on industrial output growth across SSA. These results proposed the need for home-grown policy implementation rather than a white elephant policy devoid of the country's peculiarity.

This provides the Justification for investment in economically motivated human capital skills and infrastructure to promote industrial sector growth in sub-Sahara Africa (SSA), which was highlighted in the study, especially during this period of financial belt-tightening recovery caused by the recent global pandemic. Findings disclosed poor skills acquisition and dilapidated infrastructure spread across SSA, which has mired output growth and slow industrial sector growth. This study fills a vacuum in the literature by investigating the economic effects of human capital skills and infrastructure investment on industrial sector growth in SSA through their threshold and asymmetric impact. The measurement variables were decomposed into positive and negative forms to ascertain the two regimes' short-run and long-run effects at a certain threshold. The results proffered possible ways for sustainable human capital skills and infrastructural development in SSA as part of the SDG agenda in Africa.

In summary, the emerging implications from this study provide the fundamental roadmap for policymakers on the need to prioritize investment in both human capital skills and infrastructure for sustainable industrial sector growth across individual sub-regional blocs in SSA. Hence, accomplishing some sustainable development goals (SDGs), particularly the ninth SDG towards building resilient infrastructure, promoting inclusiveness, sustainable industrialization, and fostering innovation, among others, promised in the United Nations 2030 Agenda for Sustainable Development as pronounced in 2015.

7.3 POLICY RECOMMENDATIONS

Premised on the emerging results from the study, it was clear that timely policy support is pertinent to improving industrial output growth in SSA. Therefore, the following policy recommendations were suggested thus;

Firstly, an ideal policy for factors determining industrial output growth promotes general industrial sector growth across SSA. However, the performance of the outcomes from factors determining industrial output growth in SSA is alarming, and there is a need for complete re-configuration of the education and real sectors' financial priority. Based on the current situation, a tiny percentage of the countries' budgets were devoted to the education sector and infrastructure development, and most of the SSA countries' fiscal allocations devoted to education development are usually far below the 25% UNESCO recommendation. Therefore, all stakeholders across the economic sectors should be advised to devote a certain portion of their profits after tax to support factor determinants such as school enrolment, literacy rate, access to energy and transportation being parts of the major sources of human capital skills and infrastructure development for industrial output growth. Investment banks and educational trust fund institutions should be established to manage and allocate funds to appropriate areas of need. This would improve the qualities of factors determining industrial output growth in SSA.

Secondly, findings across varied analysis methodologies from this study disclosed that school enrolment rate and average year of schooling negatively and significantly affect industrial output growth in SSA. This is contrary to the theoretical intuition of positive relationships. The negative implications might be connected to a poor education system and poor opportunity cost of schooling (i.e., an ineffective alternation between schooling ages and working ages contributed to poor productive growth). That is, the education system in SSA does not propel better alternatives for human capital skill acquisition at school and at work across different age groups. Hence, there is a need for a major policy document stipulating adequate work schedule alternation within the labour market across SSA, like its counterparts from Europe and North America. Policy of this nature would drastically improve the opportunity cost of production in the sub-region. Clearly, time constraints for work scheduled across the region should be redesigned. Wage compensation should be redesigned towards time, like their counterparts from Europe and North America, to improve work-rate efficiency and industrial output growth.

Thirdly, poor curriculum design and lack of intellectual and political will towards improving human capital skills and infrastructure might be responsible for adverse and significant effects of human capital skills and infrastructure, such as poor school enrolment rate, poor access to energy, transport, water resources, information technology, among others on industrial output growth. Therefore, necessary attention is needed in these areas to address slow output growth in the region. The government needs to make more concerted efforts through reconfiguring the entire sectors of the economy, such as the education sector, manufacturing sector, and industrial sector in the sub-region, especially across EAC ECCAS ECOWAS by allowing intellectualism and pertinent political wills to strive rather than parochial politics, as this would address current challenges of brain-drain. This would further improve human capital skills and infrastructure across EAC, ECCAS, ECOWAS and SADC. Individual sub-regional policy support should be drafted to address low human capital skills development.

Fourthly, most SSA countries' recent human capital and infrastructural indexes were relatively poor compared with other regions. The evidence released through the World Bank database for 2022 showed that only Mauritius, Seychelles and South Africa were better regarding human capital skills development out of 48 sub-Saharan countries. This calls for serious government attention to improving human capital skills and infrastructure development indexes, especially all the education, investment and productive indexes within the sub-region. There is a need for improved access to transportation and energy across the sub-regional economic groups. Some of the evidence drawn from models I, II and III under FE-LSDV in objective two were not impressive. Although access to transport-ACT and energy-ACE were statistically significant, the contribution level was low regarding unit output growth. The government should advance transportation networks and improve access to energy across the sub-regions.

Regarding sub-regional specifics, ECA, ECCAS, and ECOWAS should strive to upgrade the current means of transportation and energy sources to improve industrial output units. Specifically, transport systems linking industrial zones at the sub-regional and individual country levels should be well-equipped with the latest technology for the smooth operation of industrial activities. Also, there is a need for improved access to energy across the sub-regional economic blocs. The estimated access to energy-ACE results disclosed in model III under the second objective and NARDL models in the third objective were marginally and statistically significant in influencing industrial output growth in SSA. Therefore, government decisions to improve access to electricity, fossil fuel, machinery, etc., should be prioritised across the SSA.

Fifthly, the stakeholders need to make more serious efforts to reconfigure policy support that can strive for local and foreign investment in infrastructure across the sub-region by curtailing possible capital flight through foreign direct investment to stabilise domestic investment in critical infrastructure, as this would address current dares of poor value-added products in the region. Similarly, evidence drawn from gross capital formation, the second controlled factor for industrial sector growth, disclosed the poor degree of local investment. Productive growth can only strive where there is massive investment in factor inputs. The insignificant effect of gross capital formation in models I, II and III under the FE-LSDV and NARDLs results was unimpressive for industrial output growth in SSA. Authorities should create an enabling environment for local investment to strive. There should be massive scale of small, medium and large enterprises across the sub-region, as this would influence massive long-term output growth. Also, there is a need to re-strategize foreign investment inflows into the sub-region. Authorities should strive to attract key foreign players who can expand the current industrial sector growth through massive investments in human capital skills development and infrastructure development across the sub-region.

Additionally, there is a need for individual countries and sub-regions to follow the path of East Asia countries and regions regarding prioritizing physical and human capital development to expedite massive industrial sector growth in SSA. This would put the SSA region in a spotlight of product identity like its counterparts from abroad. Notably, different governance/public fiscal draft styles contribute to slow industrial output growth via the poor productive skill of labour and poor infrastructural spread across the sub-regions. It is pertinent for authorities in each sub-region to develop home-based policies potentially driven by the least comparative disadvantage regarding technology transfer and annexing available human capital and physical resources to expedite industrial sector growth. A prosperous industrial sector is achievable through strong political will by the authorities in SSA.

Finally, the study deduces and recommends that the ECOWAS sub-region infrastructural set-up is poor but better off regarding labour size without the sustainable skill to spur industrial sector growth. Hence, ECOWAS countries should strive to improve human capital skills through rapid policy support and investment in the education system and general well-being. ECCAS and SADC fair better regarding infrastructure but lack high-tech labour skills to match the high-tech labour demand. Therefore, the sub-regions must redesign their education curriculum and configure it to suit the demand of the current labour market. EAC is lagging behind other regions and must invest in both factor inputs. However, it can quickly adjust through rapid investment and policy support in infrastructural-tech development, where it has the least comparative disadvantage to catch up with other sub-regions regarding industrial output growth. Thus, with this assertion, the study contributes to economic science by filling the gap in the extant empirical literature.

7.4 LIMITATIONS

All empirical study has limitations. Nonetheless, the study is not free from the problem of data accessibility. Some countries in SSA lack data on some of our key variables, and they were dropped. Apart from this unavoidable challenge, forty sub-SSA countries were investigated in the study, which was very large enough to predict industrial output growth performance regarding human capital skill development and infrastructural development.

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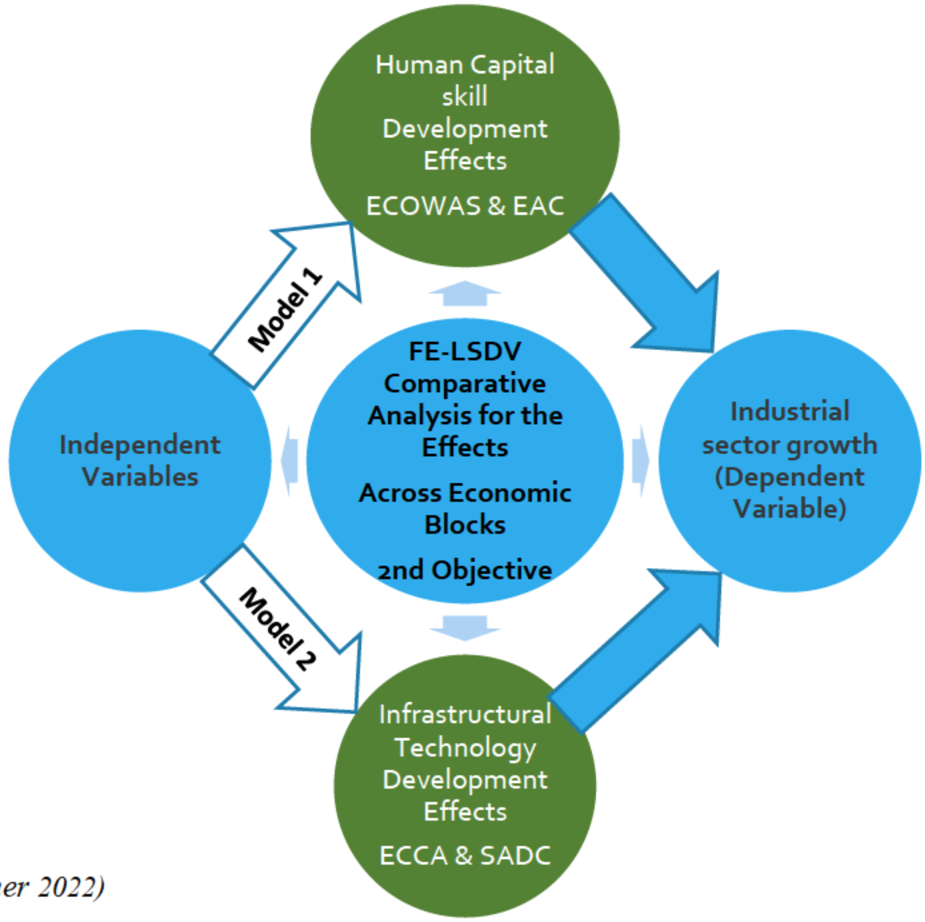
APPENDICES

Appendice One

Time Table for the Programme

S/N	Task	Period
1	Submission of the first draft of proposal	9th of September, 2021.
2	Submission of final draft of proposal	22nd of February, 2022.
3	Submission of corrected final draft of proposal	20th May, 2022.
4	Proposal Presentation	20th August, 2022.
5	Field Work	From August 2022 to February 2023.
6	Submission of first draft of the thesis	December, 2023.
5	Correction on the draft and submission of second draft	Between January and March, 2024
6	Editing of Final thesis	August, 2024.
7	Submission of thesis for examination	September, 2024.

Appendice Two



Source: *(Researcher 2022)*

Appendice Three

Theoretical Framework	Empirical/Analytical Models	The transformation of theoretical Models for Empirical Analysis
Endogenous Growth Model: Augmented model; Romer Models $Y_j = A(H)F(K_J, H_j)$……………………………..3.2 Log-linearizing model 3.2; $logY_j = logA + logH + logK_j +, logH_j + U$……….3.3 $Y_{i,t} = logA_{i,t} + \alpha logK_{i,t} + \beta log\mathrm{h}_{i,t} + \beta logL_{i,t} + u_{i,t}$ … … … … . .3.4 (Built from augmented model of Rebelo, Mankiw, Romer, and Weil, 1992)	System General Methods Moments (GMM): For Empirical Analysis: IDO=F(GCF,GEX_E,$GEX_{H,}$ LPR,LBF,LIE,HCO) Y=(IDO i.e Idustrial Added Value),A=GCF, K=GEX_{EH}, h=LPR, L=LBF, L=LIE, U= other inexplicable/stochastic factors	$logIDO_{i,t} = \beta_1 logGCF_{i,t} + \beta_2 logGEX_{Ei,t} + \beta_3 logGEX_{Hi,t} + \beta_4 LPR_{i,t} + \beta_5 logLBF_{i,t} + \beta_6 logLIE_{i,t} + \beta_7 logHCO + u_{i,t}$
Endogenous Growth Model: The Uzawa-Lucas and Cobb-Douglas Arguments $\mathrm{h}_{i,t} = logY_{i,t} - \beta logL_{i,t} + \alpha logA + \alpha logK_{i,t} + u_{i,t}$ … … 3.9	LPR=F(GCF,GEX_E,$GEX_{H,}$ LBF, LIR, SER, IDO) A=GCF, K=GEX_{EH}, h=LPR, L=LBF, U= other inexplicable/stochastic factors, (LIR, SER as other determinants of human capital) IDO, as interactive va, LBF as control va; LPR look @ Ss Labour out LBF).	$LPR_{i,t} = \beta_1 logGCF_{i,t} + \beta_2 logGEX_{Ei,t} + \beta_3 logGEX_{Hi,t} + \beta_4 logLBF_{i,t} + \beta_5 LIR_{i,t} + \beta_6 SER_{i,t} + \beta_7 logIDO_{i,t} + u_{i,t}$
Endogenous Growth Model of "learning by doing" the AK model Arguments $L_{i,t} = logY_{i,t} - \beta log\mathrm{h}_{i,t} + \alpha logA + \alpha logK_{i,t} + u_{i,t}$ … … … … . . 3.12iii	LBF=F(GCF,GEX_E,$GEX_{H,}$LPR, LIR, SER, IDO, INF, FDI EXC, INT) Y=IDO, A=GCF, FDI, K=GEX_{EH}, h=LPR, L=LBF, U= other inexplicable/stochastic factors, IDO as interactive va, (INF, EXC, INT as mediating va). (LPR,LIR, SER as control va of LBF)	

		$logLBF_{i,t} = \beta_1 logGCF_{i,t} + \beta_2 logGEX_{Ei,t} + \beta_3 logGEX_{Hi,t} + \beta_4 LPR_{i,t} + \beta_5 LIR_{i,t} + \beta_6 SER_{i,t} + \beta_7 logIDO_{i,t} + \beta_8 INF_{i,t} + \beta_9 logFDI_{i,t} + \beta_{10} EXC_{i,t} + \beta_{11} INT_{i,t} + u_{i,t}$

UNIVERSITY OF KWAZULU-NATAL
INYUVESI YAKWAZULU-NATALI

06-03-2024
Mr Sunday Anderu Keji (219090963)
School Of Acc Economics&Fin
Westville

Dear Mr Sunday Anderu Keji,

Original application number: 00019666
Project title: The effects of human capital and infrastructural development on industrial sector growth in sub-Saharan African economies.

Exemption from Ethics Review

In response to your application received on 05 March 2024 , your school has indicated that the protocol has been granted **EXEMPTION FROM ETHICS REVIEW.**

Any alteration/s to the exempted research protocol, e.g., Title of the Project, Location of the Study, Research Approach and Methods must be reviewed and approved through an amendment/modification prior to its implementation. The original exemption number must be cited.

For any changes that could result in potential risk, an ethics application including the proposed amendments must be submitted to the relevant UKZN Research Ethics Committee. The original exemption number must be cited.

In case you have further queries, please quote the above reference number.

PLEASE NOTE:
Research data should be securely stored in the discipline/department for a period of 5 years.

I take this opportunity of wishing you everything of the best with your study.

Yours sincerely,

[redacted]--------------
Prof Claire Lauren Vermaak
Academic Leader Research
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