Infrastructural Development and Real Sector Performance in ECOWAS Countries: An Aggregated and Disaggregated Approach

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Declaration

I, OKOH**,** John Onuwa do hereby declare that this thesis is entirely my own work and composition. I, OKOH**,** John Onuwa further declare to the best of my knowledge that the work embodied in this thesis has not been previously submitted in any form whatsoever for any other degree. All references made to the works of other persons have been duly acknowledged.

…… ……

OKOH**,** John Onuwa Date

Certification Page

We certify that this research thesis titled 'Infrastructural Development and Real Sector Performance in ECOWAS Countries' carried out by OKOH**,** John Onuwa **PG/ECO/170069** is adequate in scope and content for the award of Doctor of Philosophy degree in the Department of Economics, Banking & Finance, Faculty of Social and Management Sciences, Benson Idahosa University, Benin City, Nigeria.

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Dedication

This research work is dedicated to Aaliyah, Amelia, Alicia, Aurelia, and Gloria. For their love, care and understanding.

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Abstract

This study examined the effects of infrastructural development on real sector performance in the ECOWAS region from 2000 to 2021 using the aggregated and disaggregated approaches. While taking the real sector to mean the aggregation of the agricultural and manufacturing sector performance, infrastructural development was measured using the following indices: access to electricity; transport index; access to ICT services; access to water; land area available for agriculture (% of total land). Other control variables include capacity utilization, foreign direct investment and financial sector development. The broad objective of the study was to examine the impact of infrastructural development on aggregated real sector performance in the ECOWAS region. The specific objectives include: to determine the effect of infrastructural development on aggregated real sector performance in the ECOWAS countries, to ascertain the impact of infrastructural development on disaggregated agricultural sector performance in the ECOWAS region; to determine the impact of infrastructural development on agricultural sector employment in the ECOWAS region; to evaluate the impact of infrastructural development on disaggregated manufacturing sector performance in the ECOWAS region and to examine the impact of infrastructural development on manufacturing sector employment in the ECOWAS region. Secondary time series data were used for the study and they were sourced from World Development Indicators (WDI) and the Africa Infrastructure Development Index (AIDI). Five models were specified to capture the broad objective and the specific objectives respectively. The estimation process began with a descriptive statistics of the data set. A panel unit root test was conducted using the Levin, Lin & Chu test. A Pedroni co-integration test was also conducted to ascertain the existence of long run relationships among the variables. Thereafter, the generalized method of moments (GMM) estimation technique was used to estimate specified models. The results of the estimation indicate that the impact of infrastructural development on real sector performance is not statistically significant in the short run. In the long run, the result revealed that infrastructural development exerted a positive and significant effect on real sector performance in the ECOWAS region. The short run results of the disaggregated agricultural sector performance; agricultural sector employment; disaggregated manufacturing sector performance; and manufacturing sector employment indicated that the effect of infrastructural development is not statistically significant, while it was shown to be positive and statistically significant in the long run. Based on the above findings, this study recommends that policy makers, leaders and Governments in the region should ramp up efforts towards building regional infrastructures like power, transport, ICT, water and agriculture related infrastructures since the results of this study shows that it enhances real sector performance. The study therefore concludes that adequate infrastructural development is a veritable tool for stimulating real sector performance and employment generation in the ECOWAS region.

CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

Developing countries of Africa are desirous of attaining sustainable productivity and utmost economic performance. The real sector which is seen as a highly productive segment of the African economy is pivotal to the attainment of these objectives (Alliance for a Green Revolution in Africa, AGRA, 2017). The real sector directly or indirectly plays a crucial role in the welfare of a significant number of the population. For the purpose of this study, the real sector is taken to mean an amalgam of the agriculture and manufacturing sector. The Sustainable Development Goals Report, (2020) emphasize the importance of infrastructural development in facilitating manufacturing and agriculture value added.

As an important mechanism to industrialization, infrastructure is not only a causal factor driving growth but also provides necessary support for sustaining growth and increase competiveness (Kisman & Tasar, 2014). Provision of infrastructure such as road, electricity and information communication technology (ICT) has been shown to boost productive activities and thus create conducive environment for sustainable economic activities (Edeme, Nkalu, Idenyi & Arazu, 2020). In the view of Bhattacharya, Oppenheim and Stern (2015) and World Bank (2018), efficient infrastructure is crucial and effective towards the attainment of sustainable economic development. Hence, effective transport leads to timely delivery of goods and services at affordable price, while supporting the movement of workers to the most appropriate jobs. Strong Information and Communication Technology, (ICT), enable the quick stream of information, which drives overall economic efficiency (African Development Bank, AfDB, 2016). By the means of high-speed internet connections, people could enrich their knowledge and skills

through multifarious resources and expose individuals to various cultural values. Ekeocha, Ogbuabor and Orji (2022) notes that investment that improves access to infrastructure ultimately supports positive changes in socio-economic development. Apart from improving accessibility, infrastructure development brings along trade and investment opportunities to previously unconnected areas. It also provides access to goods, services, and employment opportunities through the multiplier effects. World Bank (2014) and Lanjouw (1995) earlier reiterated that the provision of infrastructure encourages investment in less developed areas, allows wider movement of goods and people, facilitates information flows and helps to commercialize and diversify the economy. Infrastructure also contributes to environmental sustainability and employment generation.

In recent past, West African sub - region maintained a relatively steady growth rate. For example in 2018, the region experienced growth rate of 4.2% which further rose to 5.2% in 2019, and further up to 5.3% in 2021 and 5.7% in 2022 (African Economic Outlook, 2020). This may not be unconnected with improving infrastructure in the region. However, between some of the countries of the sub region, there were disparities in economic growth. For instance, Benin economic growth rate slowed from 6.9% in 2019 to 2% in 2020 then to 5.2% and 5.9% in 2021 and 2022 respectively. Burkina Faso - economic growth rate slowed from 5.7% in 2019 to 0.8% in 2020 then to 4.3% and 5.5% in 2021 and 2022 respectively. Côte d'Ivoire - economic growth rate slowed from 6.2% in 2019 to 2.3% in 2020 then to 5.7% and 6.5% in 2021 and 2022 respectively. Gambia - economic growth rate slowed from 6.1% in 2019 to -0.92% in 2020 then to 5.5% and 6.7% in 2021 and 2022 respectively. Ghana - economic growth rate slowed from 6.5% in 2019 to 0.9% in 2020 then to 4.7% and 5.9% in 2021 and 2022 respectively. Guinea Bissau - economic growth rate slowed from 4.5% in 2019 to -2.4% in 2020 then to 3.0% and

4.1% in 2021 and 2022 respectively and Liberia - 2.5% in 2019, -3.0% in 2020, 3.3% and 4.8% in 2021 and 2022 respectively. For Nigeria, economic growth rate fluctuated between 2.2% in 2019, -1.8% in 2020, 2.7% in 2021 and 2.4% in 2022. Senegal - economic growth rate slowed from 4.4% in 2019 to 0.8% in 2020 then to 5.1% and 6.1% in 2021 and 2022 respectively.

In spite of the positive growth rate reported in several countries, the agricultural sector, which accounts for nearly 60% of the working population of the sub-region, continues to be characterized by declining productivity and low value addition. Available statistics from World Development Indicators (2020) indicates that in Benin Republic, growth in agricultural value stood at 23.5% in 2004 before increasing to 26.5% in 2005. In 2011, the sector experienced a decline in growth rate of 25% before increasing marginally to 25.7% in the following year. Between 2017 and 2021, the sector recorded average growth of 27.1%. Similar situation was reported for Nigeria where the growth in agricultural value added was 21.4% in 2000 to 24.5%, 36.9%, and 33.8% in 2001, 2002 and 20003 respectively. The sector witnessed the higher growth rate of 22.3% in 2001 and experienced continued decline to 14.9%, 14.0% and 14.8%, 15.8% and 15.0% in 2017, 2018, 2021 and 2022 respectively. As noted by the AfDB (2019), the unemployment problem and the doubling of food prices between 2019 and mid - 2022, which has further deteriorated due to population growth and climate change, calls for great concern. The rise in world food prices in recent times, which threaten to reverse the benefits of efforts put into poverty reduction, further exposes the need for more frantic effort to be put into the agricultural sector. World Bank (2020) has also highlighted the importance of agricultural productivity in poverty reduction. This is supported by reports of the Food and Agriculture Organization, FAO, (2018) which shows

that about 850 million people are malnourished. Human beings depend on food for survival, and so the demand for agricultural produce either in its raw or processed form will likely be on the increase. Given this overwhelming importance of the agricultural sector, investments into this sector may be one which could answer the question of sustainable employment in West African economies.

In the same vein, the poor performance of the manufacturing sector, evaluated at less than 10% of the sub - region's GDP has led to limited generation of value added and productive employment. The New Growth theories place immense emphasis on home grown sufficiency arising from deliberate development of the manufacturing sector of developing economies of which the ECOWAS region is inclusive. Few nations have been able to grow wealth and develop without adequate investment (physical or otherwise) in the manufacturing sector. Afolabi and Laseinde (2020) notes that the manufacturing sector tends to be export oriented and labour intensive at early stages. This condition subsequently gives way when investments in the sector bring about expansion of the value addition capacity. In the sub - region, manufacturing sector productivity grew by an annual average of 3.1% between 2005 and 2018 and attained its peak of 8.7% in 2010. The sector witnessed a decline in 2020 and 2021 due to the impact of COVID – 19 pandemic. The growth recorded in last decade in the region's manufacturing sector productivity was marginal due to the inability of the sector to turn comparative edge to comparative advantage which is critical to improving manufacturing value added and employment within the subsector.

World Bank (2020) concluded that efforts to achieving sustainable employment would be futile if no improvement was made in the area of real sector productivity and growth. West African countries continue to struggle to attain the sustainable development goals as economies making it

up are still categorized as under-developed or developing economies. In support of this, Adesina (2017) reiterated the importance of infrastructural development, noting that they help to boost productive activities. Unfortunately, agriculture and manufacturing productivity in West Africa countries has not been optimal, as the sector which employs a large number of the working population, continues to operate with rudimentary equipment that limits productivity and incomes of its large working population (World Bank, 2010). Patel and Obeng (2014) also observed that infrastructural facilities including power, transport, water and telecommunications are the underpinnings of every development undertaking affecting the quality of life of people.

Most economies in Africa depend on agriculture and mineral resources for their growth and sustenance. The growth originating from agriculture is four times more effective in reducing poverty than the growth coming from non-agricultural sectors (World Bank, 2010, AGRA, 2017). Unfortunately, too, most mineral resources are fast depleting and some of them non-renewable. For this reason, various economies are promoting economic diversification, as overdependence on one sector may endanger the stability of a nation's economy.

Infrastructure improvements boosted growth in the ECOWAS region by one percentage point per capita per year during the last decade, due to improvements in information and communication technology (ICT). Inadequate power infrastructure held growth by 0.1% (World Bank, 2013). Raising the region's infrastructural development levels to that of Mauritius could boost real sector performances by 5%. An overview of infrastructure in the 15 ECOWAS countries reveals that the region ranks consistently behind Southern African across many indicators. However there seem to be some form of parity in access to water, sanitation and power. ECOWAS has a well-developed regional road network, though attention is needed at the sea corridors and ports. (The infamous Apapa grid lock in Lagos Nigeria comes to mind). Surface transport is expensive

and unreasonably slow due to cartelization, restrictive regulations and delays. It was only recently that the AfDB made a financial commitment of over 1.6 billion USD for the construction of Lagos-Abidjan express way to ease the movement of persons and goods in the spirit of Continental Trade Agreement. There is no regional rail network within the ECOWAS region. Nigeria in recent history is experiencing some development in the rail transport sector. Air transport has improved in the region despite the lack of a strong. 'hub-and-spoke' structure, though safety and operational bottlenecks remain an issue. In the area of electricity, electrical power in the region and by extension Africa remains the most expensive and least reliable. Available data reveals that electricity supply reaches about 50% of the population but meets less than 30 percent of demand (Ranganathan & Foster, 2019) Improvements in ICT have been tremendous in the region in the last decade, but price for critical ICT services have been relatively high. New projects in the ICT sector are underway and are aimed at improving services and providing greater access. Improving ECOWAS's infrastructure development will require sustained spending of over 1.5 billion USD annually for a decade with about one-third going to power.

Studies conducted by World Bank (2010), amongst others agree that there are basic foundations which ought to be laid to ensure that other efforts put into agriculture and manufacturing sectors, as well as other sectors, yield results that can steer an economy towards path of prosperity. The foundations, as it concerns the real sector, may be laid in areas that include, but not limited to, improvements in infrastructure such as provision of reliable power supply, transport, access to water, sanitation and information technology.

The relationship between infrastructure and economic performance is well documented in literature - Adam (2020), David and Grobler (2020), Leng, Ma, Tang and Zhu (2020), Cheng,

Chien and Lee (2020), Wang, Lim, Zhang, Zhao and Lee (2020), Orji, Ogbuabor, Anthony-Orji, Okoro and Osondu (2020); Ogbuabor, Eigbiremolen, Orji, Manasseh and Onuigbo (2020); Orji, Nwosu, Anthony-Orji and Mba (2016) - At several levels, infrastructure is required for both agricultural and industrial development to improve income and levels of productivity. It is a widely held view that investments in infrastructure have immediate and lagged effect on job creation due to its spill over effects on other economic opportunities. Luger, Butler and Winch (2013) held that while infrastructure, through the services it supplies, supports manufacturing activity in various ways, innovations in infrastructure also stimulate innovations in manufacturing. Although studies have examined the effect of infrastructure on the productivity of the agricultural sector and manufacturing sector respectively - for manufacturing sector - Umofia, Orji and Worika (2018); Nnyanzi, Kavuma, Sseruyange and Nanyty (2022); Azolibe and Okonkwo (2020); Efobi and Osabuohien (2016); Shinyekwa and Ntale (2017); Anyanwu (2017) and Anyanwu (2018); Edeme, Nchege and Idiota (2020b), etc. for the agricultural sector Edeme *et al* (2020a); Chhachhar, Qureshi, Khushk and Ahmed (2014); Kehunde and Agwu (2015); Chikaire, Anyoha, Anaeto and Orusha (2017); Manjunath and Kannan (2017), etc. - there is obvious inadequate empirical evidence on the effect of infrastructural development on aggregated real sector performance in the ECOWAS countries. There is, therefore, the need to examine the nexus between infrastructural development and real sector performance using both aggregated and disaggregated approaches in a panel of countries with respect to ECOWAS countries which previous studies have not considered in terms of scope of countries and time including data dimension.

1.2 Statement of the Problem

The real sector of the economy forms the main driving force of the economy. It is the engine of economic growth and development. In spite of its importance, however, the performance of the real sector in terms of growth rate has been unacceptably low within the ECOWAS sub region; its contribution to GDP which is between 45% and 51% has not made any reasonable increase over the years. Essentially, the real sector relies on the stock of infrastructure for medium and long term productive activities. Insufficient Infrastructural development may compound the problem of rising cost of the working capital, thereby reducing the impact of infrastructure in the performance of the real sector.

Towards improving infrastructure in ECOWAS region, several programmes have been introduced. Generally, several policies have been adopted towards establishing regional infrastructure. They include; the Program for Infrastructure Development for Africa (PIDA) which was designed to support the African Union Abuja Treaty and the Africa Economic Community, the Africa Infrastructure Country Data (AICD), endorsed by the New Partnership for Africa's Development, NEPAD, the Development banks and several other Agencies and more recently, the West African Power Pool (WAPP) which comprises of 14 West African states aiming to ensure flow of electricity throughout West Africa from countries with cheaper, cleaner and more abundant energy resources. The key focus areas of aforementioned programs were to provide new analysis and means of putting existing continental infrastructure initiatives together to provide a common framework for African stakeholders to build the infrastructure necessary for more inclusive and regional power (energy), transport, ICT and water networks to boost trade, ignite growth and create jobs (Patel & Obeng, 2014). Access to electricity was estimated as 52% in 2018 with shortages of more than 80 hours per month. Despite this,

electricity in the ECOWAS region is among the costliest globally and it is given at about $0.25 per kilowatts (kWh), more than twice the global average (World Bank, 2018).

In telecommunication, there was the need for the development of a reliable and modern regional Telecoms broadband infrastructure including the INTELCOM II programme, alternative broadband infrastructures and sub marine cables as well as the establishment of single liberalized telecoms market. ICT improvement has been the major area of improvement among all areas of infrastructural development in Africa in the past decade (AIDI, 2016). Patel and Obeng (2014) reports that the percentage of people living within the range of a mobile signal in Africa increased from 5% in 1999 to 57% in 2006. Today, much more than four hundred million people in Africa are subscribers. Mobile telephony (provision of telephone services to phones which can move about freely) grew tremendously within the period 2010 to 2020 (and still growing) and this growth has been attributed to enormous investments and involvement of the private sector and the growth of Public-Private Partnerships (PPPs). Some mobile network providers in ECOWAS countries include MTN, Airtel, Orange, ETISALAT, among others. Reports of AfDB (2019) show that improvement in ICT service provision increased notably in 2012 and has since been on the rise. Number of subscribers and internet users increased tremendously, however, broadband connectivity (high speed internet access) has not increased alongside subscribers. Fibre broadband networks, that is network that can handle a very large volume of data and with high signal strength than standard broadband, is still poor and behind the pace of global development. Ghana, Mali, Nigeria and Senegal have recorded large improvements in fixed and mobile telephony as well as internet use relative to other regions in recent years. Countries such as Niger and Sierra-Leone however still lag behind in the area of ICT usage (AfDB, 2019). Patel and Obeng (2014) notes that high speed of interconnection is necessary for better communication

for farmers, students, businessmen, etc., hence reducing transportation costs for various individuals and businesses.

Transport infrastructure cut across infrastructure in the ports sector, rail networks, air transport system and the road networks. AfDB (2019) reports that the cost of moving goods in ECOWAS region is high relative to other regions and also more time consuming. Moreover, there is the implementation of multimodal transport infrastructure and policies to promote physical cohesion among Member States and to facilitate the movement of persons, goods and services within the region with special emphasis on increased access to island and land-locked countries.

Despite these several efforts, the performance of the real sector in various countries in the region has been erratic and on the decline. Between 2000 and 2008, the average share of the manufacturing sector in ECOWAS region was 14.7% of GDP. This declined to an average of 10.4% of GDP between 2010 and 2014 (World Bank, 2016). Manufacturing investment declined to 56.44 billion Naira in 2020 from 257.65 billion Naira recorded in 2019, indicating a decline by 201.22 billion Naira. Meanwhile, unsold inventory increased by 43.5% in 2020 compared to 2019. World Bank (2020), notes that the poor state of infrastructure in many parts of Africa may have reduced the employment potentials by as much as 40%.

Previous attempts made to ascertain the impact of infrastructural development on real sector performance dwelt on either the manufacturing sector, Umofia, Orji and Worika (2018); Nnyanzi, Kavuma, Sseruyange and Nanyty (2022); Azolibe and Okonkwo (2020); Efobi and Osabuohien (2016); Shinyekwa and Ntale (2017); Anyanwu (2017) and Anyanwu (2018); Edeme, Nchege and Idiota (2020b), etc. or the agricultural sector (Edeme *et al* (2020a); Chhachhar, Qureshi, Khushk and Ahmed (2014); Kehunde and Agwu (2015); Chikaire, Anyoha, Anaeto and Orusha (2017); Manjunath and Kannan (2017), etc. There seem to be paucity of

empirical works on infrastructural development real sector performance nexus in the ECOWAS region. The aforementioned studies adopted the disaggregated approach. (That is, examining the effect of infrastructural development on either the agricultural sector or manufacturing sector respectively). This study adopted both the disaggregated and aggregated approach (that is, jointly examining the effect of infrastructural development on both the agricultural and manufacturing sector) in determining the impact of infrastructural development on real sector performance in the ECOWAS region while taking the real sector to mean an amalgam of the agricultural and manufacturing sector as well as employment in these sub - sectors. Again, majority of the previous studies examined were country specific: Nigeria- Edeme *et al* (2020b); Ebuh, Ezike, Shitile, Smith and Haruna (2019); Adedeji Kehinde and Agwu (2015); Umofia *et al* (2018); Chikaire, Anyoha, Anaeto and Orusha (2017); Ogunleye, Ajibola, Enilolobo and Shogunle (2018); Philipines - Llanto (2012); India - Badiani and Jessoe (2017); Zambia - Ali Jabeen and Nikhitha (2016); Abokyi *et al* (2018); Kenya-Kiprono and Matsumoto (2014); Pakistan – Ahmed (2016); Mbugua and Miua (2017); USA – Abiad, Furceri and Tapalova (2016). Not much has been done at the regional level (ECOWAS) in terms of infrastructural development-real sector nexus. This study, therefore, examined this relationship based on panel of ECOWAS countries. This current study brings with it, the novelty of determining the infrastructural development - real sector nexus using the aggregated and disaggregated approach in a panel of ECOWAS countries. This is an approach neglected by previous studies.

Over the past decade and a half, West Africa has experienced rapid economic growth at an average annual rate of 5.5%. Also, series of infrastructure have been initiated and completed but since 2008, the share of real sector (agriculture and manufacturing) in GDP across the region has stagnated at around 10% and declining. This calls to question the effect of infrastructural

development which is considered vital for sustained output and employment in the long run. Motivated by this, this research sought to provide answer to the following research questions.

1.3 Research Questions

Emerging from the statement of the problem, the following constitute the questions that this research work provides answers to.

i. To what extent does infrastructural development affect aggregated real sector performance in the ECOWAS region?

ii. What is the effect of infrastructural development on disaggregated agricultural value added in the ECOWAS region?

iii. To what extent does infrastructural development contribute to employment in agriculture sector in the ECOWAS region?

iv. What is the effect of infrastructural development on disaggregated manufacturing value added in the ECOWAS region?

v. To what extent does infrastructural development contribute to employment in manufacturing sector in the ECOWAS region?

1.4 Objectives of the Study

The broad objective of this study is to examine the effect of infrastructural development on real sector performance in ECOWAS region. The specific objectives are to:

i. determine the effect of infrastructural development on aggregated real sector performance in the ECOWAS region;

ii. determine the impact of infrastructural development on disaggregated agricultural sector performance in the ECOWAS region;

iii. ascertain the influence of infrastructural development on employment in agriculture sector in the ECOWAS region;

iv. determine the effect of infrastructural development on disaggregated manufacturing performance in the ECOWAS region;

v. evaluate the impact of infrastructural development on employment in manufacturing sector in the ECOWAS region.

1.5 Hypotheses of the Study

Arising from the objectives, the study is guided by the following hypotheses stated in the null forms:

H_{01}: Infrastructural development has no significant impact on aggregated real sector performance in the ECOWAS region;

H_{02}: Infrastructural development has no significant impact on disaggregated agricultural sector performance in the ECOWAS region;

H_{03}: Infrastructural development has no significant influence on employment in agriculture sector in the ECOWAS region;

H_{04}: Infrastructural development has no significant effect on disaggregated manufacturing sector performance in the ECOWAS region;

H_{05}: Infrastructural development has no significant impact on employment in manufacturing sector in the ECOWAS region;

1.6 Significance of the Study

This study is relevant in numerous ways to several individuals and groups. The study provides empirical evidence for governments of the individual countries studied, government at the regional level, policy makers, private investors, students and researchers on the effect of the different forms of infrastructure considered in this study, on a sector crucial for food security, poverty reduction and sustainable employment in the ECOWAS region. Policy makers especially

in the area of economic planning will be guided by this work as it will suggest directions of investment which government needs to make and what infrastructural facility is needed for increased value addition from the real sector and for general economic growth. Private investors in the real sector will be guided by this work in making demands from government in the area of inputs and facilities that would ensure advancement of the sector's performance. Students will benefit from this study as it will provide information on infrastructure and real sector nexus in ECOWAS region. Other researchers will benefit tremendously from this research work which contributes literature to a path not often taken by researchers due to data constraint. The work provides country by country effects, as well as the overall effect of infrastructural development in ECOWAS region, thus satisfying both individual country's needs and regional needs.

1.7 Scope of the Study

The study examined the effect of infrastructural development on real sector performance, in terms of output and employment in both agriculture and manufacturing sectors in the ECOWAS region which is a region in the West of the African continent. The study made use of the following countries in the region: Benin, Burkina Faso, Cape Verde, Chad, Côte d'Ivoire, Equatorial Guinea, The Gambia, Ghana, Guinea, Guinea Bissau, Liberia, Mali, Niger, Nigeria, Senegal, Sierra Leone and Togo. These countries belong to the same economic category and have similar manufacturing, agricultural, political and social environment. The infrastructure considered were access to electricity, transport infrastructure, information and communication technology, water infrastructure and agricultural infrastructures. The study covered the period 2000-2021. The choice of this period is based on availability of data, especially data on infrastructure. The study is a panel - based analyses to ensure that both the time and cross-sectional effects were accommodated.

1.8 Limitation of the Study

The main limitation of this study is data related. The study relied on data extracted from both the World Development Indicators (WDI) published by the World Bank and Africa Infrastructure Development Index (AIDI) published by the African Development Bank. Likely errors from these backgrounds are possible though the integrity of the sources minimizes such. High frequency data such as quarterly data would have been most preferred as it will increase the number of observations and reduce the problem of data smoothing inherent in annual time series data. Regrettably, since quarterly data are not available for most of the variables, the study, therefore, employed annual time series data for the analysis.

1.9 Organization of the Study

This research work, however, is divided into five chapters. Chapter one is introduction. It is made up of background of the study, statement of the problem, research questions, objectives of the study, hypotheses of the study, significance of the study, scope of the study, limitation of the study and organization of the study. Chapter two dwells on review of the relevant conceptual, theoretical and empirical literatures as it affects the area under review as well gaps in the existing literature. Chapter three covers research methods. It comprises of theoretical framework, model specification and justification, estimation technique and procedure, and sources and measurement of data used for the study. Chapter four covers stylized facts, result presentation and analysis, test of hypothesis and policy implication. Chapter five is the concluding part of the study and it is made up of summary of findings, recommendation, and contribution to knowledge, agenda for further studies and conclusion.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction.

This chapter undertakes an examination of the conceptual issues, theoretical and empirical literature of the association between infrastructural development and real sector performance in the ECOWAS countries of Africa. It begins with the review of the conceptual literature, theoretical foundations on which the theoretical arguments of the link between real sector performance and infrastructural development are based. Next, a review of empirical evidence on such relationship was carried out. Thereafter, a synopsis of the evidence from practice on the link between infrastructural development and real sector performance was undertaken with a view to identifying the existing gaps in literature.

2.2 Conceptual Literature

2.2.1 Real Sector

There is no unanimity as to the composition of the real sector in extant literatures. Various authors, depending on the prevailing circumstance, have defined the real sector in different perspectives. The Central Bank of Nigeria, CBN (2012), disaggregated real sector output classification in line with the production boundary System of National Accounts (SNA) into five major sectors – agriculture, industry, building and construction, trade and services. This classification underscores the vital roles that the aforementioned sectors play in economic advancement. Yaqub (2010) and Falana (2019), while investigating the relationship between exchange rate variations and real sector performance in Nigeria considered the real sector to be agriculture, industry/manufacturing and the service sectors.

For the purpose of this study, the real sector is taking to mean combined manufacturing and agriculture sector performance (aggregated manufacturing and agriculture value added, percentage of GDP).

$$\frac{Agricultural\ and\ amanufacturing\ value\ dded}{GDP}$$

The real sector of the ECOWAS region has arguably been the brain behind the region's economic transformation over the years. From the primitive agrarian economy that it was in time past, the real sector in the region has metamorphosed into an emerging industrial workhouse. The issues of real sector performance in the sub - region has been intricate and is reflective of a mix of domestic as well as international characteristics. The real sector consists of agriculture, industry, wholesale and retail, building and construction and the service sector. The performance of this sector is largely hinged on the capacity of the private sector to catalyse real sector activities in order to achieve desirable levels of growth. Following from the above, real sector as portrayed in this research encompasses agriculture, manufacturing output and employment. Agriculture and manufacturing sector employment refers to the number of people of working age who are engaged in any activity to produce goods or provide services for pay or profit within the manufacturing and agricultural sectors at a particular time. Given the natural endowments in terms of arable lands, lakes and rivers and the climate in the ECOWAS region, the agricultural sector plays a vital role in the economy of the sub region. The sector employs a vast majority of the population in the region, provides food and essential raw materials for industries. Again, member States of the ECOWAS region identify the manufacturing sector as a driver of economic growth, development and capable of creating employment for the teeming population in the

region. This realization necessitated the adoption of the aforementioned sectors as the real sector in this study. It is one of the major components of the West Africa economy. This sector is one of the sectors that is capable, if vibrant, of fast-tracking economic growth and development coupled with high level of massive employment creation.

The real sector of the economy forms the main driving force of the economy (Okoh, 2022). It is the engine of economic growth and development. Essentially, real sector performance entails agricultural and manufacturing value added as well as employment in these sub-sectors. Improvements in the real sector propel economic growth in the ECOWAS region.

2.2.2 Infrastructural Development

Infrastructural development is used to describe improvement in physical and non-physical infrastructure that is vital to a country's economic development. It entails the provision of electricity, transport, information and telecommunication technology, irrigation and others for the enhancement of agricultural and manufacturing production. Infrastructural development is a key driver for economic progress and a critical enabler for productivity (Patel & Obeng, 2014; Lokesha & Mahesha, 2016; 2017).

Economic development theorists have identified infrastructure as critical in agriculture and manufacturing productivity. According to AfDB (2020), investment in infrastructure accounts for over half of the recent improvements in economic growth in Africa and has the potential to contribute even more. It is for this reason that infrastructural development across West African countries remains paramount to the African Development Bank's mission as contained in its High 5's transformative agenda, for the period, 2015-2025. Torrisi (2009) classified infrastructure into two components: a long lasting capital good, that is, a good originated by investment expenditure which is technically indivisible and has a high capital-output ratio; and a

public and/or merit good which exhibits the attributes of being non-excludable and non-rival. It is a concept which encompasses a variety of facilities and systems fundamental for enhanced societal living and necessary for the economy to function. It also encompasses components including physical structures used by several industries as inputs in the production process (Chan, Forwood, Roper & Sayers, 2009).

Infrastructural projects, according to Satish (2007), involve huge initial investments, long gestation periods, high risk and low rate of returns on investment, and as a result are rarely provided by private individuals but largely provided by the public sector, the world over. Bottini, Coelho and Kao (2013) in Luo and Xu (2018) noted that infrastructure affects aggregate output directly through the sector's contribution to GDP formation and indirectly by raising total factor productivity through its reduction of cost thus ensuring efficient use of other inputs. In a further classification, Ngcobo (2012) decomposed infrastructure into hard and soft infrastructure. Hard infrastructures are the tangible structures and facilities such as transport systems, telecommunication systems, energy and basic services. Soft infrastructure includes non-tangible services that provide support to the operation of hard infrastructure. Examples of soft infrastructure are policies, government mechanisms, and institutional framework. Nadeem, Mushtaq and Javed (2011), also classified infrastructure into social infrastructure (education and health) and physical infrastructure (roads, electrification, research and development, irrigation, market development, among others).

Further classifications were made by Llanto (2012), following which physical infrastructure may be divided into two groups: (i) water supply and sanitation sectors and (ii) other sectors including energy, irrigation, telecommunications and transportation sectors because infrastructure affects agricultural development through different channels. Water supply and sanitation influences the

health status of rural dwellers and their productivity as it will contribute to the physical well-being of rural dwellers and the improvement of rural human capital that contributes to higher worker (agricultural) productivity. The second group of physical infrastructure (electricity, telecommunications, irrigation and transportation) directly impacts on productivity by providing farmers and rural households with feasible options for production, processing, marketing and distribution. Bottini, Coelho and Kao (2013) listed economic infrastructure to include social utilities such as transport, energy, water and digital communications. In a similar vein, Warner and Kahan (2008) gave agricultural infrastructure to include infrastructure that aids on-farm production (irrigation, energy, transportation, pre and post-harvest storage), ensures efficient trading and exchange including telecommunications, adds value to the domestic economy like agro-processing facilities, and enables produce to move efficiently and quickly from farms to processing facilities and to wholesalers.

2.2.3 Transport Infrastructure

Transport infrastructure refers to infrastructure as structure upon which transport operations take place. This includes roads, railways, airports, harbours, pipelines, interchange facilities and the associated dedicated power and communication systems. To have an efficient and effective transport system, it is important that institutional arrangements, capital and human resources, as well as policies regarding them are in place. Paved road, according to AfDB (2013), are road surfaces with crushed stone (macadam) and hydrocarbon binder or bituminized agents, with concrete, or with cobblestones. Number of paved roads in units of inhabitants/population is a means of measuring the access of the population to road networks which are needed for the transportation of farm produce from farm gates to storage facilities, warehouses, markets, etc. AfDB (2013) report that roads are more utilized for transportation in Africa than for other means.

Agricultural inputs are transported majorly through roads from the farm gates, through processors, warehouses, sellers to consumers.

2.2.4 Electricity

Electricity is simply given as a form of energy which can be carried by wires and used for heating, lighting, and providing power for machines. Electricity use over time is typically measured in watt per hours (W/hr). Watts describe how electricity is being used, say by a small device. Kilowatts measure amount of electricity used by large appliances or a household. 1,000 watts equal 1 kilowatt (kWh). Megawatts (MW) are used to measure the output of a power plant or electricity required by an entire city. 1 MW = one thousand kWh = one million watts. Gigawatts (GW) measure the capacity of large power plants or a combination of power plants. 1 GW = one thousand MW = one million kilowatts = one billion watts (Ranganthan & Foster, 2019). Electricity can be produced from different sources: hydroelectricity (electricity produced by generators that are pushed by the movement of water), geothermal power (electricity produced using heat coming from within earth), solar power (electricity produced using the heat/energy from the sun), tidal energy (electricity generated from large amounts of energy within the ocean tides i.e. rise and fall of sea level), wind power (electricity generated through mechanical power provided by turbines turned by air flows), bio-fuels and biomass (energy generated from agricultural residues, animal waste, human waste, etc.). Electricity can also be produced from fossil fuels such as coal, crude oil, natural gas, etc.

Electricity is a form of agricultural input as it can be used to power machinery such as water pumps, certain storage facilities, grinding, drying machines, refrigerators, ventilators, conveyor belts, etc. These means of preserving agricultural produce are important as they enable producers store their output and sell them when market prices are good, thus adding value to output and

preventing wastage. Livestock production also involves the use of electricity in mechanized milking, pasteurizing and cooling of dairy products, poultry and egg production, etc. Electricity is also used for irrigation to power sprinklers. It is preferred to using diesel because it is cheaper not only because of the equipment, but also because of fuel costs. Rural electrification increases access to electricity in the rural areas and thus encourages rural dwelling. It induces movement of people and firms and increases economic activities including agriculture in these electrified rural areas (Ranganthan & Foster, 2019).

2.2.5 Information and Communication Technology (ICT)

ICT is the integration of telecommunications (wireless signals and telephones), computers, enterprise software, middle wares and audio-visual system (e.g. radio and television) which enable user's access, store, transmit and manipulate information. Mahyideen, Ismail and Hook (2012) categorized ICT into traditional technologies (radio and television) and new technologies (phone, computer and internet). A composite index of ICT as used in this work is statistics that covers estimated number of internet users and total number of phone subscriptions in a country, both fixed telephone lines and mobile cellular telephone subscriptions in a given year.

2.3 Theoretical Review

Several models and theories have been propounded by advancement theorists on the role of technological innovations on productivity and growth. Some of these theories include:

2.3.1 Solow Growth Model

The classical Solow growth model was proposed by Solow and Swan (1956). It is a model developed in an attempt to explain the differences in growth within a country over time and across countries at a given time (Romer, 2012). The model specifies a production function using

three variables output (Y), capital (K) and augmented labour (AL) and the relationship is expressed as follows:

$Y_t = f\ [K_t, A_{(t)}\ L_{(t)}]$ 2.1

The model posits that variations in output are brought about by differences in capital and differences in effective labour. The production function exhibits constant returns to scale which permits the modelling of the production function in per capita form. Solow's conclusion however is that the accumulation of physical capital cannot account for the differences in growth in output per person over time and across countries. According to Bajo-Rubio (2000), the Solow growth model serves as a foundational growth model and when augmented by the inclusion of other productive factors has been widely accepted to roughly explain cross country differences in growth of per capita income.

Infrastructural facilities which are major capital projects of an economy can be seen as capital (stock) as used in the Solow model. Thus applying this theory not wholly to the entire economy but the agricultural sector using capital and labour inputs as used in Cobb-Douglas production function adopted by the Solow model would reveal variations in output brought about by differences in capital and differences in labour.

2.3.2 The New Growth Theory

The New growth theory propounded by Romer (1987) links output with factor inputs and technological innovation. According to the theory, the relationship between output considering factor inputs and technological innovation can be represented technically as:

$AGE = q\ (T.C.I)$ 2.2

Where T = technology, C is capital stock, I = technological innovation while AGE denotes the output (employment). Aschauer (1989) estimated production function of the form:

$$AGE = AK^{\alpha} L^{\beta} G^{\Upsilon} \quad 2.3$$

2.3.3 Science-Based Agricultural Development Model

The Science based agricultural development model focuses on three major areas: the use of high pay off inputs, development of efficient technologies considering the countries' resource endowment and institutional development that aids the operation of the above two. The second point means that technologies are to be developed with a country's particular resource price ratio in mind. Tagar and Shah (2012) reiterate that developing countries must produce technologies to exploit the use of their relatively cheap input. Most of the inputs required by this model such as the land tenure system, irrigation, labour, high yielding varieties, fertilizer, pesticides, mechanical power and credit, all have to be purchased or accessed from the non-agricultural sector. The model, therefore, relies on the physical, biological, management and social sciences to produce and disseminate new technologies and guide institutional development and government in the provision of the proper environment for optimal agricultural output and productivity growth.

2.3.4 The High Input Payoff Model

This model as developed by Schultz (1965) was very prominent in the 1960s as it addressed the inadequacy of policies based on previous models such as the conservation and diffusion models. It posits that the major way to transform a traditional agricultural sector into a productive source of economic growth is through investment designed to make modern high payoff inputs available to farmers in poor countries. Despite the assumed rationality of peasant farmers, they remain poor because they have access to limited technical and economic opportunities to exploit. The new, high payoff inputs, as recorded in Ruttan and Hayami (1972) can be classified into three including production of new technical knowledge by public and private sector research

institutions, development and production of new technical inputs by the industrial sector and then the acquisition and use of this new knowledge inputs effectively and efficiently by farmers. It is on this backdrop that new high-productivity and high-yielding seeds varieties and associated technical inputs and management practices developed have diffused to various parts of the world including ECOWAS countries.. The model, therefore propagates the development and use of new inputs or techniques advanced through scientific research and education for greater output of the agricultural sector.

2.3.5 The Diffusion Model

This model was built on the benefits observed from the diffusion of knowledge in certain fields of agriculture across regions. The theory posits that disparity in knowledge available to different farmers, differences in land and labour productivity of regions account for the distorted growth rates among regions (Ziberman, 2008). The means to agricultural development is therefore through more effective dissemination of technical knowledge and a reduction of the factors contributing to disparity of productivity among farmers and among regions. This model provides a foundation and major support for research and extension effort as well as adoption of ICT in farm management to ensure diffusion of known technology to farm operators in various regions.

2.3.6 The Capital-Labour Complementary Theory

This theory opines that neither capital nor labour has the monotony of positive effect on output. The theory argues that both capital (infrastructure), labour (individuals employed) complement each other's effort, that is, one succeeds because the other has been put into use. The theory points out that due to computerization, investment in labour has reduced but this has only resulted in a decrease in the benefit to be generated from the capital investment because both are complementary. There are many problems that only humans can solve and some that only

humans can do right. Also, the machines if employed need humans in most cases to operate and assist them to function. The machines on their own part contribute to productivity by saving time, energy and increased quantity of output. This theory therefore argues that capital and labour are necessary for increased productivity and therefore a balance should be created in the employment of labour and technology (Jhingan, 2003)

2.4 Empirical Review

2.4.1 Studies on Infrastructural Development and Agriculture Sector Performance

Infrastructural development enables the availability of goods at relatively cheaper rate. This is based on the Science - based agricultural development theory which emphasizes the use of high and efficient technology to enhance productivity. The theory opines that the development of physical infrastructure helps to accentuate optimal agricultural productivity. Rural infrastructure tends to raise agricultural productivity thus inducing growth in the rural areas, thereby bringing about higher agricultural wages and employment opportunities. A number of studies have examined the impact of infrastructural development on agricultural output/performance and agricultural employment with varying outcomes.

Constant and Shijun (2012) examined Benin agricultural productivity and profitability 1961 to 2008 and found no significant effect of infrastructure, including agricultural research, extension, as well as foreign direct investment on agricultural productivity. These findings were made in the assessment of agricultural productivity and major driving factors. The study made use of the Ordinary Least Squares (OLS) technique of estimation. It also found labour and government effectiveness to have negative effects on productivity while agricultural land and rainfall had positive effects on productivity.

Ngcobo (2012) studied the impact of infrastructure on agricultural economic development in Bizana, Eastern Cape using both qualitative and quantitative data and analysis, it was revealed that farmers are faced with a number of infrastructural challenges including inadequate access to water, shortage of dams, absence of storage facilities, insufficient health facilities and transport systems especially road network. The state of the local roads determines the quantity of produce to be harvested and transported by the farmer, and the poor state of roads reduces the income generated by the farmers. It recommended that the fundamental infrastructure, which forms the foundation for the agricultural sector and enables the sector to be in sync with other sectors, be prioritized, adding that, it is important that infrastructure such as roads are in a good condition, for poor access can easily discourage potential investors, and thus reduce agricultural output and further dampen economic growth.

Similarly, a study conducted by Llanto (2012), on the impact of infrastructure on agricultural productivity in the Philippines 1981 to 2010 using the Generalised Least Squares (GLS) method of estimation, has its empirical results indicating significant link between rural infrastructure and agricultural productivity. Electricity and roads are significant determinants of agricultural productivity with rural roads providing important connectivity with growing markets and lessening input costs and transaction costs of rural producers and consumers. Access to electricity also creates opportunities for rural households to earn income.

Rabirou, Ayanwale, Idowu, and Williams (2012) ascertained the effect of rural transportation system on agricultural productivity in Oyo State, Nigeria. To assess the influence of rural transportation on food farmer's productivity, a random sample of 230 respondents was selected and data collected on their socio-economic and farm specific characteristics. Descriptive statistics, Herfindhal Index and Technical Efficiency Approach were used to analyse the data.

The results indicate that majority of food farmers were in their middle age with mean age of 50 years and most of them used one plot at a location between 5 and 10km to their village of residence. They acquired land by inheritance and practiced intensive crop diversification as risk management strategy. The transportation modes used in addition to walking include bicycle, motorcycle, and car with increasing trend in the use of motorcycle. The mean Technical Efficiency (TE) of food farmers was 0.82 with significant inefficiency effects. The inefficiency analysis indicates positive effect of distance, crop diversification and un-tarred type of road on farmer's productivity, while poor level of education among farmers, use of bicycle; trekking and weekly working time negatively affect farmer's efficiency. The negative effect of trekking and use of bicycle and the excess working time suggest the adoption of more IMT of motorized type to optimize farming time and increase farmer's productivity.

Adepoju and Salman (2013) examined access to infrastructure and its effects on agricultural productivity in Surulere and Ife East Local Government Areas (LGAs) of Oyo and Osun States, South West, Nigeria. The data collected for the study were analysed using descriptive statistics and total factor productivity model to explain the effects of the available infrastructure on the farmers' productivity. The total factor productivity model used revealed that farm size and labour were positive and significantly affected productivity at 5% and 1% levels of probability respectively. It was however observed that the contribution of female labour in Ife East LGA was higher than that of male, thus introducing gender productivity differential into the production process. With regards to the infrastructural elements, improvement in soil practices and extension visits had positive significant effects on productivity and were statistically significant at 5 % level of probability in both LGAs. It is recommended that more infrastructures be provided to further improve the agricultural productivity of the rural farmers.

Kiprono and Matsumoto (2014) implemented a difference-in-difference estimation to assess the impact of the change in road access on agricultural productivity of smallholder farmers in Kenya 2004 to 2012. Findings suggest that, since road access improvement occurs more in poorer road access areas, investment in rural road infrastructure enhances the productivity of rural farmers.

At the international level, Chhachhar, Qureshi, Khushk and Ahmed (2014) examined the impact of ICT on agricultural sector productivity in Pakistan. The study summarized the connection and relevance of ICT in agricultural productivity revealing that various forms of information technology provide information to farmers in Pakistan. The study adopted the content analysis methodology and covered the period 1990 to 2012. In the remote areas, the radio serves as a tool for broadcasting many agriculture programs. Televisions also serve this purpose. Mobile phones reduce the gap between farmers and buyers. Internet access permits farmers to get latest information concerning weather conditions as well as information concerning price and the marketing of their goods. These services allow farmers to receive and access information and knowledge needed to enhance productivity and output. The study was centred primarily on the agricultural sector and relied on qualitative method of research.

Adedeji, Kehinde and Agwu (2015) examined the effect of applying ICT to the agricultural sector. Adopting the qualitative research method, respondents were drawn from a group of students, farmers and traders in Ogun and Lagos States of South West Nigeria. The study found that though the support of government was necessary in improving the fortunes of the agricultural sector, introduction of ICT enhanced agricultural productivity in the period under review. Just like Chhachhar, Qureshi, Khushk and Ahmed (2014), the study was centred primarily on the agricultural sector and relied on qualitative method of research.

For ICT, Ali, Jabeen and Nikhitha (2016) looked at its impact on agricultural productivity in Zambia for the 2014 - 2015 farming season spanning from December 2014 to April 2015. The study selected farmers using the multiple stage random sampling technique and analysis was also made using the Ordinary Least Square Regression Techniques. Findings showed that the impact of television on productivity was positive and statistically significant. Farmers in the age group of 25-40 years were more productive due to use of more ICTs. The use of ICTs along with seed, fertilizer and amount borrowed showed a positive impact on agricultural productivity, but no significant impact of ICTs with seed, fertilizer, and amount borrowed and level of education on net profit per acre was found. The study recommended development of ICT skills for agricultural extension workers and farmers. It also called for the development of an agricultural information system which would provide information about farming techniques, market information, etc.

Manjunath and Kannan (2017) examined the effect of rural infrastructure on agriculture productivity in the states of Karnataka 1981 to 2010. The study adopted the random effect method of analysis, and findings show positive effect of rural infrastructure on agriculture productivity. The study was based on a particular region in India. It did not capture the entire Indian economy, and as such limited in terms of national policy implication.

Focusing on electricity, Badiani and Jessoe (2017) investigated the issue of electricity prices, groundwater and agriculture as well as the environmental and agricultural impacts of electricity subsidies in India 1995 to 2004 using panel data methodology. Findings from the detailed district panel data analysis showed that agricultural electricity subsidies contributed to groundwater over-exploitation and indeed increased agricultural production through irrigation.

Chikaire, Anyoha, Anaeto, and Orusha (2017) studied the effect of ICT use on agricultural practices and welfare of farmers in Imo state, South East of Nigeria during the farming season of

2014 - 2015. Adopting the qualitative research method, the results of the study revealed that ICT is beneficial and applicable to agriculture and also helps to improve farmers' welfare.

Investigation of the effects of road transport infrastructure on agricultural sector development in Nigeria 1985 – 2014 was conducted by Ogunleye, Ajibola, Enilolobo and Shogunle (2018) using the OLS estimation technique and Granger Causality test. The result shows that a positive relationship exists between road transport infrastructure and agricultural sector development and a unidirectional causality run between them.

Ebuh, Ezike, Shitile, Smith and Haruna (2019) re-examined the link between infrastructure development and output growth in Nigeria for policy formulation and implementation. The paper employed the Granger causality test based on the time series vector error correction model (VECM) to reinvestigate the nexus between infrastructure investment and economic growth in Nigeria, using quarterly data from 1997:Q1 to 2017:Q4. The study, therefore, interrogates and accepts the infrastructure–growth hypothesis that increased financial infrastructure and infrastructure stock stimulates long-run real economy expansion in the Nigerian context. The study failed to indicate the sectors at which infrastructural development policy was targeted. Every economy is made up of various sectors. Economic growth is brought about by growth in these sectors.

In Nigeria, Edeme, Nkalu, Idenyi and Arazu (2020a) examined the effect of infrastructural development on agricultural output and employment in Economic Community of West African States (ECOWAS) 2000 - 2017 utilizing panel autoregressive distributed lag (PARDL) methodology. The study found that infrastructures that support agriculture productivity foster employment creation. The results show that information and communication technology positively affect agricultural output while access to electricity has positive effect on agricultural

employment. Transport infrastructure had negative and insignificant effect on agricultural performance. The study concluded that investment in infrastructural development with a view to improving agricultural productivity potentially contributes to employment generation. This study was centred on the agricultural sector. An agriculture sector led growth alone cannot propel the performance of the real sector of the region to an all-inclusive growth.

Empirical evidence has shown that agricultural trade has been affected mostly positively by infrastructural development. Al-Maamari (2021) in 25 selected North and Latin American countries 2006 to 2014 examined the potential impacts of hard infrastructure development on agricultural trade using the gravity model of trade and Tobit estimator. The results showed that the quality of hard infrastructure networks is important for agricultural trade revealing that ports infrastructure had the highest effects on trade volume while railroad infrastructure had the lowest.

2.4.2 Studies on Infrastructural Development and Manufacturing Sector Performance

The developed and developing world alike count industrialization as a significant factor for growth and development, and the relationship between infrastructure and industrialization in any economy can be appreciated from the perspective of distribution of resources which include production inputs and outputs to and from industries. Thus, infrastructure and industrialization go hand in hand in the quest for sustainable development in any economy. The connection shared by infrastructure and industrial sector growth is undeniable. The multiplier effect expressed by industrial output thanks to infrastructure (for example, energy infrastructure) begs the need for infrastructural development in any economy. Thus, the significance of infrastructure to the industrialization in any economy cannot be emphasised. Its enhancement is relevant to the survival of the industrial sector.

At the global level, Ahmed (2016) examined the role of social infrastructure on manufacturing firms' productivity for Pakistan. Using the OLS methodology on firm level data on productivity taken from census of manufacturing industries, CMI, 2005 to 2006 for various districts, the study found that social infrastructure exerted a positive influence on manufacturing in the urban areas and negatively in the rural areas.

Efobi and Osabuohien (2016) studied the effect of infrastructure on manufacturing export in ECOWAS. Applying the OLS estimation technique on data covering the years 2000 to 2012, the study found that infrastructure has no significant effect on manufacturing exports and has a negative effect when interacted with both government effectiveness and control of corruption.

The main concern of the study by Mesagan and Ezeji (2016) was to determine the effect of both economic and social infrastructure on manufacturing performance in Nigeria 1980 to 2014 using the ARDL methodology. Findings indicate that capital education expenditure and telecommunication had positive and significant effect on manufacturing performance while health expenditure and electricity had negative and insignificant effect on manufacturing performance.

In a study to ascertain the effect of infrastructure on manufacturing export in East African Countries, Shinyekwa and Ntale (2017), using the panel ARDL methodology, found that economic infrastructure (hard, more than soft infrastructure) generates huge gains in terms of export of manufactured products. The study covered the period 2001 to 2014.

Still on Africa as a region during the period 1990–2011, Anyanwu (2018), using the IV-SLS technique with year and sub - regional fixed effects, found that social infrastructure has variant effects on manufacturing output. While Primary education has an inverted U-shaped relationship and Secondary education has a negative significant relationship, it is only tertiary education that

is found to exhibit a significant positive association. Conversely, the author does not find any significant role of ICT infrastructure, proxy by mobile phone and fixed phone subscriptions. Among the other factors, trade openness, FDI stock, social and political globalization, and energy use intensity are found to exhibit differential impacts. An earlier study by the same author (Anyanwu, 2017), focusing on North Africa 1990 - 2011 and following a similar technique, however, results among other findings indicate that ICT infrastructure/technology, trade openness and inward stock of FDI exert significant positive effect on manufacturing value added output, while the converse is found true for political globalization, and civil violence, inter alia.

A study on the impact of infrastructural development on the manufacturing sector in Ghana by Abokyi *et al.* (2018) spanning a period 1971–2014, however, reveals results obtained from the ARDL Bounds test, in confirmation of the hypothesis that infrastructure development in terms of electric consumption negatively impacts manufacturing sector output. The author attributes this finding to the continuous nose-diving in the average share of industrial sector's electricity consumption in Ghana.

In Nigeria, Umofia, Orji and Worika (2018) analysed the effects of infrastructure on the industrial sector performance of Nigerian economy 1980 to 2016 using dynamic ordinary least squares methodology. Industry value-added was used as an indicator of Nigeria's industrial sector performance, while electricity supply, gross capital formation, and federal government spending on transport and communication were used as indicators for infrastructural development. The results of the study showed that electricity supply exerted a positive but insignificant impact on industry value-added; gross capital formation and federal government spending had a positive and significant impact on industry value-added (on a 5% confidence level). The study recommended that measures to revamp and maintain the power sector of

Nigeria must be taken seriously to ensure better supply of power. The study went further to recommend the curbing of corruption and the disbursement of funds for infrastructural development. It is also essential to monitor the disbursed funds to ensure that the project it was allocated for is carried out and that adequate infrastructure will be built and properly maintained to encourage greater level of industrial experience and performance.

A recent study by Azolibe and Okonkwo (2020), using a panel least square estimation technique on panel data of SSA region spanning from 2003 to 2018 found that the quantity and quality of telecommunication infrastructure is a major factor that influences industrial sector productivity. The authors attribute the relatively low level of industrial sector productivity in the region to poor electricity and transport infrastructure, under-utilization of water supply as well as sanitation infrastructure.

Edeme et al (2020b) examined the nexus between infrastructural development, capacity utilization and manufacturing value added in Nigeria using OLS estimation method on data from 1980 to 2019. The paper found that electricity had a negative and insignificant effect on manufacturing value added while manufacturing capacity utilization and capital expenditure had a positive impact on manufacturing value added.

In order to determine the long run implications of the effects of infrastructure development, liberalization, and governance on manufacturing production (MVA) in Sub-Saharan Africa, and for purposes of retaining estimates efficiency and consistency in the presence of complex errors, Nnyanzi, Kavuma, Sseruyange and Nanyiti (2022) employed the Panel-Corrected-Standard-Error estimator on panel data spanning 2003–2018 for 30 SSA countries. The result of this analysis shows that infrastructure development as well as governance is critical to manufacturing production. While infrastructure development affects MVA positively in the long run, an

improvement in the financial openness facilitates this linkage but only between transport infrastructures on the one hand, and electricity infrastructure on the other, whereas the converse appears the case when trade liberalization is the moderating variable. The conclusion of the study renders support to the regional efforts geared towards improving infrastructure; substantially curbing poor governance while vigorously promoting the rule of law, regulatory quality, government effectiveness, voice and accountability.

Ekeocha, Ogbuabor and Orji (2022) evaluated the effects of both aggregate and disaggregated infrastructural development indices (such as transport, electricity, ICT, and water and sanitation infrastructure indices) on economic growth in Africa. The study used the dynamic system GMM framework and found that both aggregate and disaggregated infrastructural development indices impact positively on GDP per capita growth in Africa. These impacts were shown to be significant in all cases, except for the transportation infrastructure index. The results overwhelmingly confirmed the prevalence of the symmetric hypothesis in the infrastructure–growth relationship in Africa. The study also found some evidence in support of the significant roles of capital, labour and initial GDP per capita in Africa's economic performance, while the role of trade remained negative and muted. The study concluded that through effective public administration, African leaders and policymakers can promote economic performance on the continent by evolving policies that favour increased infrastructural development, human capital development and capital accumulation.

2.4.3 Studies on Infrastructural Development and Employment.

Few studies have also investigated the effect of infrastructure on yet another real sector performance indicator, the sectorial employment, and have found mostly positive and significant effects.

Arouri, Youssef, M'Henni and Rault (2014) using panel granger causality explored the causal relationship between energy and employment on a data sample of 16 African countries covering the period 1991 to 2010. The Wald tests for testing causality revealed a unidirectional causality running from employment to energy use in 4 countries and the reverse in 2 countries. A bi-directional causality was recorded in 5 countries but no causality in 5 others.

For the USA economy, Abiad, Furceri and Topalova (2015) in a study titled Macroeconomic Effects of Public Investment: Evidence from Advanced Economies 1985 – 2015 using public investment forecast errors to identify the causal effect of government investment found that improvement in public infrastructure generally decreases unemployment rate by 0.11% in the short term and 0.35% in the medium term. In the same vein, an increase in infrastructural investment increases labour demand by 1.13% in the short term, 1.07% in the medium term, and 0.08% in the long term.

At the international level, Garcia-Murillo (2016), in a study in Latin America to estimate the impact of ICT on employment using the fixed effects regression technique on data from World Bank and International Labour Organization in a panel of 23 countries over the period 2000 to 2015, found that ICT in the form of internet and broadband subscriptions had positive and significant effects on employment. The study centred on Latin American

countries. The current study examines the infrastructural development – real sector nexus in ECOWAS countries.

At the continental level, Irungu, Mbugua and Muia (2017), adopting the content review method of qualitative research, conducted a study in Kenya which assessed the beneficial use of ICTs among youths in agriculture. The scope of the study was centred on focus group discussions that involved 19 group members drawn from the Bringo, Kiambu, Nairobi and Nakuru Counties. The study found out that ICT use in agriculture increased opportunities and motivated youths to engage in profitable agriculture.

Laborda and Sotelsek (2019), examined the effects of road infrastructures on employment, productivity and growth between 1999 and 2011 using the dynamic panel data General Method of Moments, (GMM) methodology on data for East Asia and Pacific, Europe and Central Asia, Latin America and Caribbean, Middle East and North Africa, North America, South Asia and Sub-Saharan Africa. The study organized the countries into the following: low-income countries, middle-income countries and high-income countries. Focusing on two broad categories of transport infrastructure (road density and paved road) the study found positive effects of road density and paved road on total factor productivity in low and middle-income countries and a Kuznets curve between road density and unemployment. The major limitation of this study is that it considers only road density and paved road as transport infrastructure neglecting rails, ports and air transport that make up the transport composite index used in measuring the overall impact of transport infrastructure.

In Nigeria, Edeme, *et al* (2020a) examined the effect of infrastructural development on agricultural output and employment in Economic Community of West African States (ECOWAS) 2000 – 2017 utilizing panel autoregressive distributed lag (PARDL)

methodology. It was found that information and communication technology (ICT) positively affect agricultural output while access to electricity had positive effect on agricultural employment. In addition, transport infrastructure had negative and insignificant effect on agricultural performance. This study demonstrates that infrastructure that support agriculture productivity fosters employment creation.

Nawaz, Anwar and Iqbal (2021) using district level panel data 1990 – 2020 examined the spatial effects of road infrastructure on employment while accounting for institutional quality, rural connectivity and labour productivity in Pakistan. The estimates based on the spatial regression model indicate that road density positively and significantly impacts on employment. A 10 per cent increase in road infrastructure would lead to a 4.3 per cent increase in employment directly and indirectly. The spill over effects of road infrastructure helps optimize the merits of public investment in infrastructure projects. Empirical evidence indicates that institutional framework and access to rural areas complement road infrastructure channelizing road development's employment effects.

Following the recent boom of the service sector in developing economies owing to the rise in digital technologies, Ndubuisi and Tetteh (2021) examined the effect of digital infrastructure on employment in the service sector. Employing a panel data of 45 SSA countries over the period 1996 – 2017, the paper found a positive and significant effect of digital infrastructure on the services sector employment. The study notes that the effect of digital infrastructure on the service sector is dependent on the prevailing institutional and economic conditions. Digital infrastructure is more beneficial for employment generation at the base of the pyramid. The study is centred on ICT led employment generation in the service sector. It dwells less on ICT driven employment generation in the real sector of the economy.

2.4.4 Studies on Infrastructural Development and Economic Performance.

Infrastructure affects growth via several demand and supply side channels as empirical evidence has shown. Investments in power and energy, transport and telecommunication significantly impact growth, as most types of infrastructure represent a vital input in the production of goods and services. Infrastructures can reduce the cost incurred in the course of delivering goods, facilitates the movement of persons and wares, reduce productivity bottlenecks and enhance competitiveness.

Yu, De Jong, Storm and Mi (2013) examined the heterogeneous economic impacts of transportation characteristics, with a consideration of spatial heterogeneity, across Chinese prefecture-level cities. The study made use of data from 237 Chinese cities from 2000 to 2012; a random-parameters model is applied to account for the heterogeneity across these cities. The estimation results indicate significant variability across cities, with the computed impacts (elasticity values) of transportation-related features (highway and railway freight volumes, highway passenger volume, urbanization rate, public transit, paved roads, and highway congestion rate) varying significantly across cities. The effects were mostly positive, except for highway congestion rate. A 1% increase in a city's highway and railway freight volumes would increase the city's gross product per capita from 0.0001% to 0.0972% and 0.0001% to 0.0254% across cities in China, respectively. While a 1% increase in highway congestion rate would decrease the city's gross product per capita by an average of 0.031%.

Luz, Dos Reis, De Araujo Leite and Moritz (2016) investigated the nexus between transport infrastructure and economic development. The paper considered a sample of the ten countries with the highest Gross Domestic Product (GDP) among them from 2010 to 2014. The study found that GDP is correlated to the Logistic Performance Index of the World Bank (LPI) using linear regression. The results indicate that there is no relationship between the two variables, but suggest that this relationship is positive when considering the GDP per capita of the ten countries surveyed. Investment in transportation infrastructure has been recognized as a crucial growth promoting strategy (Crescenzi, Di Cataldo and Rodriguuez – Prose, 2016).

In a similar study, Saidi, Shahbaz and Akhtar (2018) studied the impact of transport energy consumption and transport infrastructure on economic growth by utilizing panel data on MENA countries (the Middle East and North Africa region) for the period of 2000–2016. The MENA region panel is divided into three sub-groups of countries: GCC panel (containing the Gulf Cooperation Council countries), N-GCC panel (containing countries that are not members of the Gulf Cooperation Council), and North African countries (called MATE—Morocco, Algeria, Tunisia and Egypt). Using the Generalized Method of Moments (GMM), we find that transport energy consumption significantly adds to economic growth in MENA, N-GCC and MATE regions. Transport infrastructure positively contributes to economic growth in all regions. The Dumitrescu-Hurlin panel causality analysis shows the feedback effect of transport energy consumption and transport infrastructure with economic growth. The empirical results add a new dimension to the importance of investing in modern infrastructure that facilitates the use of more energy-efficient modes and alternative technologies that positively affect the economy with minimizing negative externalities.

Gherghina, Onofrei, Vintila and Armeanu (2018) studied the relationship between the main forms of transport, related investments, specific air pollutants, and sustainable economic growth. Since transport may act as a catalyst for social, economic, and environmental development, the study is of great importance. Based on data retrieved from Eurostat, Organisation for Economic Co-operation and Development (OECD), and World Bank, the output of fixed-effects regressions for EU-28 countries over 1990–2016, the paper reveals that road, inland waterways, maritime, and air transport infrastructure positively influence gross domestic product per capita (GDPC), though a negative link occurred in the case of railway transport. As concerning investments in transport infrastructure, the empirical results exhibit a positive impact on economic growth for every type of transport, except inland waterways. Besides, emissions of carbon dioxide CO_2 from some kinds of transport, alongside other specific air pollutants, negatively influence GDPC. The fully modified and dynamic ordinary least squares panel estimation results reinforce the findings. Further, in the short-run, Granger causality based on panel vector error correction model pointed out a unidirectional causal link running from sustainable economic growth to inland waterways and maritime transport of goods, albeit a one-way causal link running from the volume of goods transported by air to GDPC. Also, the empirical results provide evidence that support one-way short-run links running from GDPC to investments in road and inland waterway transport infrastructure. In addition, a bidirectional short-run link occurred between carbon dioxide emissions from railway transport and GDPC, whereas unidirectional relations with economic growth were identified in the case of carbon dioxide emissions from road and domestic aviation. In the long-run, a bidirectional causal relation was noticed between the length of the railway lines, investments in railway transport infrastructure, and GDPC, as

well as a two-way causal link between the gross weight of seaborne goods handled in ports and GDPC.

Babatunde (2018) investigated the impact of government spending on infrastructure. Both primary and secondary data were used for the study. The secondary data comprised of reported annual spending on selected infrastructure and annual Gross Domestic Products for 1980 to 2016 for Nigeria. The data treatments used for the secondary data are unit root and co- integration tests using Augmented Dickey–Fuller and Phillip–Perron model. Weighted least square was used to test the sample of 37-year annual time series using vector error correction model. For the primary data, a sample of 242 respondents was utilised for the study. Statistical random sampling was used for the sample selection. The data analysis was done with descriptive statistics. Findings from the study indicate that government spending on transport and communication, education and health infrastructure has significant effects on economic growth; spending on agriculture and natural resources infrastructure recorded a significant inverse effect on economic growth in Nigeria. An element of fiscal illusion was observed in the government spending on agriculture and natural resources indicating that government is not contributing as much as the private sector in spending on agriculture and natural resources infrastructure in Nigeria.

Stawiarska (2018) tried to confirm the hypothesis that "the developed logistic and transport infrastructure of the region has contributed to the improvement of the economic performance of the region". This paper showed the relationship between the developed elements of logistic and transport infrastructures of regions (density of roads, density of railway networks, size of warehouse space, number of intermodal trans-shipment terminals, tonnage

transported in tonnes) and economic performance of regions (regional GDP, private capital productivity). The study is based on the regions of Poland with special attention to Silesia region. The results indicate that the liberalization and computerization of the TSL sector is desirable by industry leaders of the region. The findings of this paper can help TSL authorities and decision-makers leaders to make investment decisions regarding logistics and transport infrastructure.

Vlahinić, Pavlic and Mirkovic (2018) investigated the effects of transport infrastructure on economic growth in Central and Eastern European Member States (C.E.M.S.) in the period 1995–2016. During the transition period in C.E.M.S., most investments were focused on the roads, while railways have been lagging for decades. The objective of the study was to estimate the effects of transport infrastructure (road and rail) on economic growth while controlling with other variables such as population growth, gross fixed capital formation and trade openness. Panel data analysis with three standard estimators (pooled ordinary least squares, fixed effects and random effects) were used. The results show positive effects in case of all estimated variables, except the railway infrastructure where the effects seem to be negative. The results revealed the long-standing problem of inefficient and outdated railway infrastructure. The paper supports the European Union's guidelines for the need to invest in railway infrastructure to ensure effective transport in the long term, create competitive advantages, reduce greenhouse gas emissions and thus simulate sustainable economic growth in C.E.M.S.

In the same vein, Cigu, Agheorghiesei and Toader (2019) examined the link between the transport infrastructure and the economic performance in the EU-28 countries, over the

period of time 2000–2014, using panel data methods. The results show significant effects from transport infrastructure components even after institutional and other factors are controlled for. From the path analysis results, the study confirmed the alternative hypothesis, outlining the unidirectional long-run causality relationship between growth, transport infrastructure and Public Sector Performance. Transport infrastructure status (proxy with index of transport) has significant impact on economic development with coefficient estimate. The public performance indicators influence economic growth. On the one hand, the corruption, the regulatory environment, size shadow economy, infant mortality, income inequality, inflation and unemployment rate negatively affect economic growth, and on the other hand there is a strong positive relationship between the quality of the judiciary, education achievement, life expectancy and economic growth.

Wang, Lim, Zhang, Zhao and Lee (2020) used dynamic spatial modelling approach to show that transport infrastructure is crucial in improving national economic growth of Brazil, Russia and India. However, in the case of East and Central Asia, Commonwealth of Independent States and South Asia countries, the study found that transport infrastructure spill over effects were significantly negative. The study which covered the period 1999 to 2019 showed that transport infrastructure exerts positive influence on growth in Central and Eastern Europe. This study also shows that there could be substantial regional differences on the growth effects of transport infrastructure.

Foreign aid has received enormous attention in the literature; however, an evaluation of how the infrastructural readiness of the host economies drives the effectiveness of aid is the main objective of this re-examination by Ogundipe, Oye, Ogundipe and Osabohien (2020). The study assesses this main thrust in ECOWAS Sub-region for the period 1995–2017 using the

system GMM estimation approach. The result shows that FDI promotes growth, though growth responded less proportionately to FDI influx. Alternatively, following the interaction of FDI and physical infrastructures, the responsiveness of FDI declined. Specifically, the responsiveness of GDP growth declined from 29.2% to 0.21% for road infrastructures. It hence becomes expedient for African government and policy makers to channel a viable development path towards enhancing transport and road infrastructures in order to attract financing into the space and the livelihood of poor rural population.

Kauzen, Sun, and Frank (2020) examined the impact of transport infrastructure on economic growth in Tanzania using statistical information from 2003 to 2018. The structural equation modeling (SEM) was employed. The study ascertained the relationship between transport infrastructure and economic growth, which shows that each construct on the final model has significant effects. Therefore, the results revealed the impact of transport infrastructure on economic growth in Tanzania. From the obtained results, the paper suggested that transportation authorities should design transportation policy, which supports the development of transport infrastructure, and that existing good transportation policy should be maintained for the continued economic growth of Tanzania. In addition, the government should encourage Public, Private Partnership (PPP) in the implementation of transportation infrastructure projects. These findings of the study provided new insights to policymakers on how to solve transport infrastructure problems, setting investment priorities and project management. Popov (2020) attempted solving the actual problem of the construction of the linear multiple regression model, establishing the relationship between the economic indicators of the Russian Federation and the logistics infrastructure of the Federal districts. The obtained equation allows the identification of the objects of the logistic infrastructure

that have the greatest impact on the dependent variables, and to assess the degree of contribution of each component to the change in the resulting variable using multiple regression analysis. The methodological tools of the study include correlation analysis, Kolmogorov – Smirnov test and multiple regression analysis. The values of the indicators are taken for the period 2004-2016. As a result of the study using the IBM SPSS Statistics 20 program, the objects of the logistics infrastructure of the Federal districts that have the greatest impact on the economic performance of the Russian Federation were identified. It is shown that the transport and logistics infrastructures of St. Petersburg, the Krasnodar Territory, the Kirov, Sverdlovsk and Novosibirsk Regions as well as the volume of imports of goods in the Stavropol Territory and the number of transport enterprises in the Republic of Dagestan have the greatest impact on the dependent variables. An increase of the dependent variables by one percentage point will lead to an increase in the economic indicators of the Russian Federation from 0.74% to 1.01%.

Cheng, Chien and Lee (2020) used GMM and principal component analysis techniques to investigate the nexus among financial development, ICT diffusion and economic growth in a panel of 72 countries. The study found that even though ICT diffusion promotes economic growth in high income economies, the relationship remained ambiguous in middle- and low-income economies. The study, however, revealed that increasing mobile usage rather than internet usage promotes growth in low- and middle-income economies, and that interacting ICT and financial development promotes growth across all income levels.

A number of studies have found interesting outcomes on the nexus between infrastructural development and economic performance - Horvat, Bendix, and Skoko (2020) demonstrated positive influence of investments in infrastructure project (electricity infrastructure) on

economic and human development in East African countries. Similarly, Ouédraogo (2010) found the existence of equilibrium relationship and feedback hypothesis between electricity consumption and economic growth in Burkina Faso, while Solarin and Shahbaz (2013) found similar patterns between urbanization and electricity consumption in Angola. In the United Arab Emirates, Shahbaz, Sbia, Hamdi and Ozturk (2014) validated this existence of cointegration and feedback hypothesis between electricity consumption and carbon dioxide emissions, while Karanfl and Li (2015) obtained similar results among Organization of Petroleum Exporting Countries (OPEC) member economies.

David (2019) found bidirectional causal relationship between telecommunication infrastructures and economic growth in selected African countries. Similarly, David and Grobler (2020) found that ICT penetration encourages economic growth in Africa. Maji and Waziri (2020) used panel data of 45 African countries to show that improvements in ICT penetration and renewable energy consumption enhance environmental sustainability in Sub-Saharan Africa (SSA). Rice and Martin (2018) found that investment in ICT infrastructure is a strategic resource for smart city infrastructure and economic improvement, which is indispensable in the development of communities, regions and urban environments in Australia.

Studies that corroborate the symmetric role that ICT infrastructures play in economic improvements in Europe are: Adam (2020) and Toader, Firtescu, Roman and Anton (2018). Lee, Kadir, Umar, Abidin and Nasirin (2017) also found symmetric effect of ICT infrastructure on growth while distinguishing between the roles of strong and weak institutions. Leng, Ma, Tang and Zhu (2020) also established symmetric relationship between ICT infrastructure and rural income diversification in China.

In developing countries, Cataldo, Pino, and McQueen, (2019) also established symmetric relationship between ICT and MSME's revenues and profits. The study also showed that company size matters so that the smaller the company the higher the ICT impact on revenue.

Some other studies have also focussed on ICT infrastructure and the Nigerian economy, and found some interesting results (Orji, Ogbuabor, Anthony-Orji, Okoro and Osondu 2020; Ogbuabor, Eigbiremolen, Orji, Manasseh and Onuigbo 2020; Orji, Nwosu, Anthony-Orji and Mba 2016).

Contrary to these studies, Akinwale, Jesuleye and Siyanbola (2013) did not find any evidence in support of the feedback hypothesis in Nigeria and the study attributed this to low levels of electricity consumption due to low generation and distribution.

Table 2.6: Tabular Summary of Empirical Literature Reviewed.

Author/Date	Topic	Place of Study	Method of Analysis	Findings
Constant & Shijun (2012)	Benin Agriculture Productivity and Profitability Measurement.	Benin Republic	OLS	Infrastructure had no significant effect on agricultural productivity.
Ngcobo (2012)	The impact of infrastructure on agricultural economic development in Bizana Eastern Cape	Bizana, Eastern Cape.	Qualitative and quantitative analysis	Infrastructures such as roads, storage facilities, water and inadequate health facilities have significant effects on agricultural output.
Llanto (2012)	The impact of infrastructure on agricultural productivity	Philippines	GLS	Electricity and road infrastructures are significant determinants of agricultural output.
Rabioru Ayanwale, Idowu & Williams (2012)	Effect of rural transportation system on agricultural productivity in Oyo state, Nigeria	Nigeria	Descriptive statistics, Herfindal Index and Technical Efficiency approach	Rural transport system enhances agricultural productivity.
Adepoju & Salman (2013)	Increasing agricultural productivity through rural infrastructure: evidence from Oyo and Osun States, Nigeria	Southwest Nigeria	Descriptive Statistic	Infrastructure has positive significant effect on agricultural productivity.
Kiprono & Matsumoto (2014)	Roads and farming: the effect of infrastructure improvement on agricultural input use, farm productivity and market participation in Kenya,	Kenya	Difference-in-difference estimation technique	Investment in rural road infrastructure enhances the productivity of rural farmers.

Source: Authors' Compilation, 2023.

Table 2.6: Tabular Summary of Empirical Literature Reviewed Continued.

Author/Date	Topic	Place of Study	Method of Analysis	Findings
Arouri, Ben Youssef, M'henni & Rault (2014)	Exploring the causality links between energy and employment in African countries.	Africa	Panel granger causality	The study revealed that there exists a unidirectional causality running from employment to energy
Abiad, Furceri & Tapalova (2015)	Macroeconomic Effects of Public Investment: Evidence from Advanced Economies	USA		The study found that public infrastructure decreases unemployment.
Adedeji, Kehinde & Agwu (2015)	Application of ICT to Agriculture as a Panacea to Unemployment in Nigeria.	Nigeria	qualitative research method	The study found that though the support of government was necessary in improving the fortunes of the agricultural sector, introduction of ICT enhanced agricultural productivity in the period under review.
Mesagan & Ezeji (2016)	The role of social and economic infrastructure in manufacturing sector performance in Nigeria.	Nigeria	ARDL	Capital expenditure and telecoms infrastructure had positive and significant effect on manufacturing sector performance while electricity infrastructure had a negative and insignificant effect on manufacturing sector performance
Garcia-Murillo (2016)	The Impact of ICTs on employment in Latin America: A call for Comprehensive Regulation	Latin America	Fixed effects	ICT in the form of internet and broadband subscription had a positive and significant effect on employment.
Ali, Jabeen, & Nikhitha (2016)	Impact of ICT on agricultural productivity in Zambia	Zambia	OLS	The use of ICT and other farm inputs showed a positive impact on agricultural productivity

Source: Authors' Compilation, 2023.

Table 2.6: Tabular Summary of Empirical Literature Reviewed Continued.

Author/Date	Topic	Place of Study	Method of Analysis	Findings
Efobi & Osabuohien (2016)	Manufacturing Export, Infrastructure and Institutions: Reflections from ECOWAS.	ECOWAS	OLS	The study found that infrastructure had no significant effect on manufacturing exports
Shinyekwa & Ntale (2017)	The Role of Economic Infrastructure in Promoting Exports of Manufactured Products: Trade Facilitation and Industrialisation in the EAC	EAC	Panel ARDL	Economic infrastructure generates huge gains in terms of manufactured products
Irungu, Mbugua & Muia (2017)		Kenya	Fixed effects regression technique	ICT use in agriculture had significant effects on employment
Chikaire, Anyaoha, Anaeto & Orusha (2017)	Effect of ICT use on agricultural practices and welfare of farmers in Imo state South East Nigeria	Nigeria	Qualitative research method	Application of ICT to agriculture benefits and improves farmer's welfare.
Manjunath & Kannan (2017)	Effects of rural infrastructure on agricultural development: A district level analysis in Karnataka, India	Karnataka State, India	Random effects	Findings show that rural infrastructure enhances agricultural productivity
Badiani & Jessoe (2017)	Electricity prices, groundwater and agriculture: the environmental and agricultural impacts of electricity subsidies in India.	India	Panel data analysis	The findings revealed that agricultural electricity subsidies contributed to groundwater exploitation and increased agricultural production through irrigation.
Anyanwu (2017)	Manufacturing value added development in North Africa: Analysis of key drivers.	North Africa	IV-SLS technique	ICT infrastructure exert significant positive effect on MVA

Source: Authors' Compilation, 2023.

Table 2.6: Tabular Summary of Empirical Literature Reviewed Continued.

Author/Date	Topic	Place of Study	Method of Analysis	Findings
Ogunleye, Ajibola, Enilolobo & Shogunle (2018)	Influence of road infrastructure on agricultural sector development in Nigeria.	Nigeria	OLS	Positive relationship exists between road infrastructure and agricultural sector development.
Abokyi, Appiah-Konadu, Sikayena & Oteng-Abayie (2018)	Consumption of electricity and industrial growth in the case of Ghana	Ghana	ARDL	Infrastructure development in terms of electricity consumption impacts negatively on manufacturing sector output.
Umofia, Orji & Worikas (2018)	Infrastructural Development and the Nigerian Industrial Sector Performance.	Nigeria	OLS	Electricity infrastructure exerted a positive but insignificant effect industry value added.
Anyanwu (2018)	Does human capital matter in manufacturing value added development in Africa?	Africa	IV-SLS technique	ICT infrastructure does not play any significant role in enhancing MVA
Ebuh, Ezike, Shitile, Smith & Haruna (2019)	Infrastructure development and output growth in Nigeria	Nigeria	Vector Error Correction Model, VECM.	Increased infrastructure financial and infrastructure stock stimulates long run real economic growth in Nigeria

Source: Authors' Compilation, 2023.

Table 2.6: Tabular Summary of Empirical Literature Reviewed Continued.

Author/Date	Topic	Place of Study	Method of Analysis	Findings
Edeme, Nkalu, Idenyi & Arazu (2020a)	Infrastructure development, sustainable agricultural output and employment in ECOWAS Countries.	West Africa	Panel autoregressive distributed lag PARDL.	Infrastructure development affects agricultural productivity positively and contributes to employment generation.
Edeme, Nchege & Idiota (2020b)	infrastructural development, capacity utilization and manufacturing value added in Nigeria	Nigeria	OLS	Electricity infrastructure had a negative and insignificant effect on MVA, while capacity utilization and capital expenditure impacted MVA positively.
Azolibe & Okonkwo (2020)	Infrastructure development and industrial sector productivity in SSA	Africa	Panel least square estimation technique	Telecommunication infrastructure influences the productivity of the industrial sector positively**.**
Al- Maamari (2021)	Infrastructure and Agricultural Trade in North and Latin America.	North and Latin America.	Tobit estimator	Infrastructural development promotes agricultural trade volume.
Nnyanzi, (2022**)**	The manufacturing output effects of infrastructure development, liberalization and governance: Evidence from SSA.	Africa	Panel-Corrected Standard Error Estimator	Infrastructure development affects manufacturing value added MVA positively**.**

Source: Authors' Compilation, 2023.

2.5 Gaps in the Existing Literature.

Apparently, the literature review has shown that several studies have examined the influence of infrastructural development on either agricultural or manufacturing sector productivity in both developed and developing countries, and of course within the ECOWAS sub-region though with varied results. While Kehinde *et al* (2015), Chikaire *et al* (2017), Badiani *et al* (2017), Ogunleye *et al* (2018), Umofia *et al* (2018), Ebuh *et al* (2019), Edeme *et al* (2020a), Edeme *et al* (2020b), Azolibe *et al* (2020), and Nnyanzi *et al* (2022), contend that infrastructural development tend to be associated with either higher manufacturing output or agricultural output. Others like Efobi and Osabuohien (2016) found that the effect of infrastructural development on manufacturing output or agricultural output is minimal. Studies like Ahmed (2016), Abokyi *et al* and (2018), Anyanwu (2018), appear to confirm negative relationship between infrastructural development and manufacturing sector productivity. The above studies adopted the disaggregated approach in examining the effect of infrastructural development on either the agricultural or the manufacturing sectors. There seem to be paucity of studies that have examined the effects of infrastructural development on real sector performance in ECOWAS countries using both the aggregated and disaggregated approaches. This provides a point of departure from existing studies and presents the gap that this current study fills. A study of this nature allows for international comparison between countries and regions thus providing an avenue for wider readership on the subject under investigation. In terms of policy formulation, the findings of these kinds of study will reinforce regional integration which is vital to the economic survival of a region like ECOWAS, given that the region has a large number of small and isolated economies and that the economic geography of the region is quite challenging.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

This chapter presents the technique the study employed in providing answers to the research questions posed. The chapter is organized as follows: first, the theoretical framework which identified the channels through which infrastructural development is expected to affect real sector performance. Next is empirical specification of relevant models; justification of the models, estimation techniques – procedures and tests; and data sources (definition and measurement).

3.2 Theoretical Framework

This study considers the real sector as an amalgam of the agriculture and manufacturing sectors. The theoretical framework for this study is drawn from the empirical works of Ebuh, Ezike, Shitile, Smith and Haruna (2019) and a modified neoclassical growth model which comprises capital, labour and infrastructure as inputs (Sahoo & Dash, 2009) and it is stated thus:

$$Y_t = f\ (K_t\, L_t\, INFR_t) \qquad 3.1$$

Where Y_t is gross output in the economy using K_t Capital, L_t labour, $INFR_t$ Infrastructure as inputs. Sahoo and Dash, (2009) notes that the production function of the form stated in 3.1 above is open to the possibility of constant returns to scale as proposed by Solow – type models (Solow 1956) even as the model admits the possibility of increasing returns to capital as argued by the endogenous growth theory (Romer, 1987). Unlike the exogenous growth model, increase in the steady state income per capita can be likened to infrastructure. The role of infrastructure in fostering real sector performance can be captured through an input production function, a refinement of the standard Cobb-Douglas production function. The Cobb-Douglas production

function was employed by Romer (1987) to re-specify the model while assuming constant returns to scale. This implies that doubling input exactly doubles output (that is $\alpha + \beta = 1$) as visualized in equation (3.2)

$$Q_t = A(K)^{\alpha} (L)^{\beta} \quad 3.2$$

This permits the modelling of the production function in per capita form as in equation (3.3)

$$\frac{Q}{AL} = f \left[\frac{K}{AL}, \frac{L}{AL}\right] \quad 3.3$$

$$q = f(k) \quad 3.4$$

Where $\frac{Q}{AL}$ is output per unit of effective labour, $\frac{K}{AL}$ is the amount of capital per unit of effective labour. Further, Q = $\frac{Y}{AL}$, k = $\frac{K}{AL}$, and $f(k) \quad = f(k-1)$

The model assumes that labour (L) grows at a fixed rate (n) and technology (A) grows at a fixed rate (g). The essence is to find out if change in capital (K) brings about changes in per capita output (Y). If the returns to capital points to its contributions to output, then variations in the accumulation of physical capital accounts for a significant part of either cross-country differences (Romer, 1987).

3.3 Model Specification

This research work specifies five basic models which were meant to capture the general objective and the specific objectives as stated in chapter 1. 4. The West African sub-region is made up of 15 Sovereign States with various common attributes as well as heterogeneous characteristics and differences in productivity levels, thus necessitating the inclusion of all the countries of the sub-region in the model. The models and their variables were chosen in line with literature - Steenkamp and Rooney (2017); and Edeme, *et al* (2020a). The forms of infrastructure considered in this study were included in order to expose their individual effects which are

expected, a-priori, to be positive because capital is a factor which affects production positively. Equation 3.1 above is therefore further modified to capture the infrastructures considered in this study and it is stated thus in equation 3.5 below:

$$Y = f\ (K, L, ELECTinfra,\ TRANSinfra,\ ICTinfra,\ WATERinfra,\ AGRICinfra.) \quad 3.5$$

Dalenberg and Partridge (1997) notes that public capital (public infrastructure) stimulates the economy in two ways: contributing to output/performance and increasing labour demand and/or supply. Therefore, in line with Yaqub (2010), Falana (2019) and Okoh (2022), this study considers the real sector as an amalgam of the agriculture value added, manufacturing sector value added (as a percentage of GDP) as well as employments in both the agriculture and manufacturing sectors respectively. This study is primarily concerned with infrastructures and real sector performance. Consequently, equation 3.5 above is further modified to include agriculture value added and manufacturing sector value added as well as employments in the agricultural and manufacturing sectors and is stated in equation 3.6 below:

$$AGRMAF_GDP = f\ (K, L, AGR_GDP, EMPLOY_AGR, MAF_GDP, EMPLOY_MAF, ELECTinfra,\ TRANSinfra,\ ICTinfra,\ WATERinfra, AGRICinfra.) \quad 3.6$$

Equation 3.6 above forms the bases for the final specification of the models for this study. We proceed to specify the models for this study in line with objectives of the study.

Model 1

This model captures objective one of this study. Based on theoretical framework posited above and following Edeme, *et al* (2020a), the relationship for empirical estimation is written functionally as:

$$AGRMAF_GDP = f\ (EMPLOY_AGR, EMPLOY_MAF, ELECTinfra, TRANSinfra, ICTinfra, WATERinfra, AGRICinfra, CU, FDI, FSD) \quad 3.7$$

In panel form, the above relationship can be rewritten in linear form as follows;

$$InAGRMAF_GDP_{it} = \varphi_0 + \varphi_{1i} \ln(EMPLOY_AGR_{it} + \varphi_{2i} \ln(EMPLOY_GDP_{it} + \varphi_{3i} \ln(ELECTinfra_{it} + \varphi_{4i} \ln(TRANSinfra_{it}) + \varphi_{5i} \ln(ICTinfra_{it} + \varphi_{6i} \ln(WATERinfra_{it}) + \varphi_{7i} \ln(AGRICinfra_{it}) + \varphi_{8i} \ln(CU_{it}) + \varphi_{9i} \ln(FDI_{it}) + \varphi_{10i} \ln(FSD_{it}) + \varepsilon_{it} \quad 3.8$$

Where $AGRMAF_GDP$ denotes combined manufacturing and agriculture sector performance - real sector performance (aggregated manufacturing and agriculture value added, percentage of GDP), $ELECTinfra$ denotes (access to electricity, as percentage of total population), $TRANSinfra$ denotes transport infrastructure (transport composite index), $ICTinfra$ denotes information and communication technology (information and communication technology composite index; percentage of individuals using the internet, fixed-broadband internet subscriptions, active mobile-broadband subscriptions, percentage of individual using computer, mobile-cellular telephone subscriptions per 100 inhabitants), $WATERinfra$ denotes irrigational facilities (volume of water available for irrigational services), *AGRICinfra* denotes agricultural infrastructures, CU denotes manufacturing sector capacity utilization (capacity utilization refers to the manufacturing and production capabilities that are being utilized by a nation or enterprise at any given time. It is the relationship between the output produced with the given resources and the potential output that can be produced when capacity is fully utilized. Capacity utilization rate is derived simply by dividing total capacity utilized over a specific period by total production capacity or optimal levels multiplying by 100, FDI denotes foreign direct investment flows in the economy (foreign direct investment net inflows, as percentage of GDP), FSD denotes combination of, access to, and efficiency of institutions to provide financial services at low cost.

It is measured by four sub-indices – financial market diversity, market liquidity, market efficiency and the institutional environment. ε_{it} denotes error term, φ_1, φ_2, φ_3, φ_4, φ_5, φ_6, φ_7, φ_8, φ_9 and φ_{10} are respective coefficients to be estimated for the respective variables: subscript *i* (i = 1,...,N) denotes the individual countries while *t* denotes time (t = 1,...,T).

Model II

Model 11 is in tandem with objective 1 which is to determine the impact of infrastructural development on agricultural value added. Following Steenkamp and Rooney (2017) and Edeme, *et al* (2020), the relationship for empirical estimation is written functionally as:

$$AGR_GDP = f\ (ELECTinfra, TRANSinfra, ICTinfra, WATERinfra, AGRICinfra, CU, FDI, FSD) \quad 3.9$$

In panel form, the above relationship can be rewritten in linear form as follows

$$InAGR_{GDP_{it}} = \varphi_0 + \varphi_{1i} \ln(EMPLOY_AGR_{it} + \varphi_{2i} \ln(ELECTinfra_{it} + \varphi_{3i} \ln(TRANSinfra_{it}) + \varphi_{4i} \ln(ICTinfra_{it}) + \varphi_{5i} \ln(WATERinfra_{it} + \varphi_{6i} \ln(AGRICinfra) + \varphi_{7i} \ln(CU_{it}) + \varphi_{8i} \ln(FDI_{it}) + \varphi_{9i} \ln(FSD_{it}) + \varepsilon_{it} \quad 3.10$$

Where AGR_GDP denotes agriculture sector performance (agriculture value added, percentage of GDP). All other variables as previously defined. ε_{it} denotes error term, φ_1, φ_2, φ_3, φ_4, φ_5 φ_6 φ_7 φ_8 and φ_9 are respective coefficients to be estimated for the respective variables, subscript *i* (i = 1,...,N) denotes the individual countries while *t* denotes time (t = 1,...,T).

Model III

This model is designed to capture objective two which is to ascertain the impact of infrastructural development on employment in agriculture sector in the ECOWAS region. In line

with variables under consideration and relying on Manjunath and Elumatai (2017) with variation, the functional form of the relationship is expressed as:

$$EMPLOY_AGR =$$

$$f(ELECTinfra, TRANSinfra, ICTinfra, WATERinfra, AGRICLinfra, CU, FDI, FSD) \quad 3.11$$

The functional form of the model can then be converted to linear model and expressed in its panel form as follows:

$$InEMPLOY_{AGR_{it}} = \varphi_0 + \varphi_{1i} \ln(ELECTinfra_{it} + \varphi_{2i} \ln(TRANSinfra_{it}) + \varphi_{3i} \ln(ICTinfra_{it}) + \varphi_{4i} \ln(WATERinfra_{it} + \varphi_{5i} \ln(AGRICinfra) + \varphi_{6i} \ln(CU_{it}) + \varphi_{7i} \ln(FDI_{it}) + \varphi_{8i} \ln(FSD_{it}) + \varepsilon_{it} \quad 3.12$$

$EMPLOY_AGR$ denotes employment in agricultural sector (employment in agriculture as percentage of total employment). All other variables are as previously defined.

Model IV

Model IV is specified to capture the effect of infrastructural development on manufacturing value added in the ECOWAS region (objective 3). In line with the variables under consideration and relying heavily on Edeme, et al (2020) with a little modification, the functional form of model is specified as:

$$MAF_GDP =$$

$$f(ELECTinfra, TRANSinfra, ICTinfra, WATERinfra, AGRICinfra, CU, FDI, FSD) \quad 3.13$$

In panel form, the above relationship can be stated linearly as follows;

$$In(MAF_GDP_{it}) = \varphi_0 + \varphi_{1i} \ln(EMPLOY_MAF_{it} + \varphi_{2i} \ln(ELECTinfra_{it} + \varphi_{3i} \ln(TRANSinfra_{it}) + \varphi_{4i} \ln(ICTinfra_{it}) + \varphi_{5i} \ln(WATERinfra_{it} + \varphi_{6i} \ln(AGRICinfra) + \varphi_{7i} \ln(CU_{it}) + \varphi_{8i} \ln(FDI_{it}) + \varphi_{9i} \ln(FSD) + \varepsilon_{it}$$

3.14

Where MAF_GDP denotes manufacturing sector value added (percentage of GDP). All other variables are as previously defined.

Model V

In line with the fourth objective of the study which is to determine the influence of infrastructural development on manufacturing sector employment and following from the study's theoretical framework, the model is expressed in its functional form as:

$$EMPLOY_MAF =$$

$$f((ELECTinfra, TRANSinfra, ICTinfra, WATERinfra, AGRICLinfra, CU, FDI, FSD)) \quad 3.15$$

In panel form, the above relationship can be stated linearly as follows;

$$In(EMPLOY_MAF_{it}) = \varphi_0 + +\varphi_{1i}\ln(ELECTinfra_{it} + \varphi_{2i}\ln(TRANSinfra_{it}) + \varphi_{3i}\ln(ICTinfra_{it}) + \varphi_{4i}\ln(WATERinfra_{it} + \varphi_{5i}\ln(AGRICinfra) + \varphi_{6i}\ln(CU_{it}) + \varphi_{7i}\ln(FDI_{it}) + \varphi_{8i}\ln(FSD_{it}) + \varepsilon_{it} \quad 3.16$$

$EMPLOY_MAF$ denotes employment in manufacturing (employment in manufacturing as percentage of total employment).

3.4 Estimation Technique

In this study, the system General Method of Moments (GMM) estimation procedure was employed for several reasons. Firstly, the system GMM controls for endogeneity in the modeling exercise by correcting for simultaneity and or reverse causality through the procedure of instrumentation, and also accounting for omitted variables that are time invariant. Secondly, the system GMM is able to restrict instrument proliferation and can control for cross sectional dependence as revealed by Tchamyou, Erreygers and Cassimon (2018) via the utilization of forward orthogonal deviations. The study applied the GMM specification of Roodman (2009a, 2009b). In the GMM regression, instrument proliferation is revealed when the number of

instruments is greater than the number of cross sections in the study. That said, a stable GMM model must have lower number of instruments as compared to the total number of cross sections. The study further tested for autocorrelation in the models using the AR(2) estimation values in the GMM models. The procedure is such that a probability value of the AR(2) greater than conventional levels of statistical significance means the absence of serial correlation in the model. Robust standard errors are also utilized to control for heteroskedasticity in the modeling exercises.

For the estimation procedure for this study, some pre-estimation tests were conducted to ascertain its suitability. They include: panel unit root test, as well as co-integration test which were considered to ascertain the suitability of the variables, the data and the technique that was employed.

3.4.1 Panel Unit Root Test

The Levin, Lin and Chu test of the common unit root was used to test for unit root in this study. The null hypothesis is stated as:

H_0: The panel series has a unit root

Rejecting the null hypothesis leads to the conclusion that the panel series is stationary. The null hypothesis is rejected if the p-value is less than 0.05 at 5% level of significance.

3.4.2 Test for Co-integration

The Pedroni (2008) test for co-integration was utilized for this. It was used to check if the variables have a long run relationship, that is, to ascertain the statistical significance of the long run coefficients. The null hypothesis is that the variables are not co-integrated; therefore, rejecting the null hypothesis implies that there is co-integration.

3.4.3 Generalized Method of Moments (GMM)

The Generalized Method of Moments (GMM) estimator was introduced by Karl Pearson in 1894 but popularized by Lars Peter Hensen in 1982 as a generalization of the moment's conditions. In econometrics and statistics, the generalized method of moments (GMM) is a generic method for estimating parameters in statistical models. Usually it is applied in the context of semi parametric models, where the parameter of interest is finite-dimensional, whereas the full shape of the data's distribution function may not be known, and therefore maximum likelihood estimation is not applicable.

Generalized Method of Moments (GMM) is an estimation procedure that allows econometric models especially in panel data to be specified while avoiding often unwanted or unnecessary assumptions, such as specifying a particular distribution for the errors. The method requires that a certain number of moment conditions be specified for the model. These moment conditions are functions of the model parameters and the data, such that their expectation is zero at the parameters' true values. The GMM method then minimizes a certain norm of the sample averages of the moment conditions, and can therefore be thought of as a special case of minimum-distance estimation.

The GMM estimators are known to be consistent, asymptotically normal, and most efficient in the class of all estimators that do not use any extra information aside from that contained in the moment conditions. The generalized method of moments (GMM) is a method for constructing estimators, analogous to maximum likelihood (ML). However, GMM uses assumptions about specific moments of the random variables instead of assumptions about the entire distribution, which makes GMM more robust than ML, at the cost of some efficiency. The assumptions are called moment conditions.

GMM generalizes the method of moments (MM) by allowing the number of moment conditions to be greater than the number of parameters. Using these extra moment conditions makes GMM more efficient than ML. When there are more moment conditions than parameters, the estimator is said to be over-identified. GMM can efficiently combine the moment conditions when the estimator is over-identified.

GMM is also an instrumental variable (IV) estimator, since it uses instrumental variables to meet the moment conditions. However, it is important to note that the conventional IV estimator (though consistent) is, however, inefficient in the presence of heteroscedasticity (Ullah, Akhtar & Zaefarian, 2018). The common practice currently when facing heteroscedasticity of unknown form is to use the Generalized Method of Moments. GMM makes use of the orthogonality conditions to allow for efficient estimation in the presence of heteroscedasticity of unknown form. Efficient GMM brings with it the advantage of consistency in the presences of arbitrary heteroscedasticity which has become an 'omnipresent' problem in empirical work (Baum, Schaffer & Stillman, 2002). Therefore, an important advantage of using GMM is that they allow researchers to control for unobservable heterogeneity, that is, systematic differences across cross-sectional units.

One of the common problems associated with panel data analysis is endogeneity bias, which can lead to inconsistent estimates and incorrect inference. Inconsistency and incorrect inference provide misleading conclusions as well as inappropriate theoretical interpretations. In some serious cases, endogeneity bias can lead to wrong signs for coefficients.

Endogeneity in regression analysis which is a condition in which explanatory variable(s) correlate with error term can originate from different sources, which include measurement errors,

omitted variables and simultaneity issues (Ullah, Akhtar & Zaefarian, 2018). One method that has proven to deal with the problem of endogeneity compared to other estimators is the GMM. The GMM estimator provides consistent results in the presence of the different sources of endogeneity (Wintoki, Linck & Netter, 2012). In application to real life data and panel data analysis, the GMM estimates have uniformly smaller standard errors than Weighted Least Square (WLS), which in turn are much smaller than the Ordinary Least Square (OLS) standard errors.

The GMM remove endogeneity by internally transforming the data. In this way, the number of observation is reduced and the process enhances the efficiency of the GMM model (Wooldridge, 2012). There are two types of transformation methods, viz, first difference transformation, also known as one step GMM, and the second difference transformation (two step GMM). The one step GMM involves a process in which the past value is deducted from its current value. One main limitation of the approach is that if a variable recent value is missing, it could result in loss of too many observations (Roodman, 2009). On the other hand, the two step GMM involves the application of forward orthogonal deviations. This means that the approach perform its transformation by subtracting the average of all the future available observations of a particular variable (Roodman, 2009). In this way, unnecessary loss of data is prevented, which makes the two step GMM superior to the one step GMM. According to Arellano and Bover (1995), in the case of balance panel dataset, a two-step GMM provides more efficient and consistent estimate for the involved coefficient.

Although the GMM estimator has been adjudged to yield consistent estimate even in the presence heteroscedasticity, its efficiency however depends on the validity of the instrumental variables. Instruments can be internal instruments or external instruments. External instruments

involve the use of external variables that correlate with the endogenous variables and orthogonal to the error term. The internal instruments involve the use of variables within the data set as instruments. However, there is usually great difficulty in obtaining variables suitable as external instruments. Greene (2008) suggested that suitable instruments come from within the data set. In this case lagged difference $(y_{it-1} - y_{it-2})$ and lagged level y_{it-1} can serve as valid instrument since they satisfy the two conditions for valid instruments and moreover they are easily available.

On this basis, this study adopts the two stage GMM using internal instruments. The lagged values of explanatory variables are used as instruments. To test for the validity of the instruments, the J Statistics is adopted. The decision rule is that if the probability value of the j statistics is greater than 0.05, then the instruments are valid.

3.5 Sources of Data, Definition and Measurement

Data used for this study were sourced from World Development Indicators (WDI) published by World Bank, and Africa Infrastructure Development Index (AIDI) published by African Development Bank. The variables for the study are defined in table 3.1 below;

Table 3.1: Definition of Variables

Variable	Definition of Variables	Measurement	Source of Variable	Sign	Source of Data
$AGRMAF_GDP$	combined manufacturing and agriculture sector performance - real sector performance	aggregated manufacturing and agriculture value added, percentage of GDP	Okoh (2022); Falana (2019); Yaqub (2010)	Positive	WDI (2021)
AGR_GDP	Agriculture value added	Agricultural value added (% of GDP).	Edeme *et al* (2020a)	Positive	WDI (2021)
$EMPLOY_AGR$	Agriculture employment	Employment in agriculture (% of total employment)	Edeme *et al* (2020a)	Positive	WDI (2021)
MAF_GDP	Manufacturing value added	Manufacturing value added (% of GDP).	Edeme *et al* (2020b)	Positive	WDI (2021)
$EMPLOY_MAF$	Manufacturing employment	Employment in manufacturing (% of total employment)	Edeme *et al* (2020a)	Positive	WDI (2021)
$ELECTinfra$	Electricity infrastructure	Access to electricity (% of population)	Edeme *et al* (2020a)	Positive	AIDI (2021)
$TRANSinfra$	Transport infrastructure	Transportation composite index.	Edeme *et al* (2020a)	Positive	AIDI (2021)
$ICTinfra$	Information and communication technology infrastructure	ICT composite index	Edeme *et al* (2020a)	Positive	AIDI (2021)
$WATERinfra$	Water reservoir, boreholes and irrigational facilities	volume of water available for irrigational services	Azolibe & Okonkwo (2020)	Positive	AIDI (2021)
$AGRICinfra$	Agricultural land	Agricultural land (% of land area)	Edeme *et al* (2020a)	Positive	WDI (20201
CU	Capacity Utilization	Capacity utilization rate is derived simply by dividing total capacity utilized over a specific period by total production capacity or optimal levels multiplying by 100.	Edeme *et al* (2020b)	Positive	WDI (2021)
FDI	Foreign direct investment flows in the economy.	Foreign direct investment in the economy net inflows, as percentage of GDP	Edeme *et al* (2020a)	Positive	WDI (2021)
FSD	Financial sector development	financial market diversity, market liquidity, market efficiency and the institutional environment	Author's initiative	Positive	WDI (2021)

Source: Author's Compilation, 2023.

CHAPTER FOUR

PRESENTATION AND DISCUSSION OF RESULTS

4.1 Introduction.

This study examined the nexus between infrastructural development and real sector performance in ECOWAS countries. The estimation process began with an examination of time series properties of the selected variables. A number of pre-estimation tests were carried out. The GMM was used to determine the relationship existing between infrastructural development and real sector performance. In this chapter, however, we present stylized facts on the nexus between infrastructural development and real sector performance in ECOWAS countries; as well as the presentation, analysis and the discussion of results of the study and other findings; test of hypotheses and draw out from our finding, those policies that will be of immense help to policy makers. The result presentation began with the descriptive statistics which examined the distribution of the data for the analysis. This is followed by examination of the time series properties of the data using panel unit root test and co-integration test. The essence of the test for stationarity and co-integration is to ascertain the order of integration of variables, as well as ascertain the existence of long run relation if the variables are not integrated of order zero. The estimation results as well as test of hypotheses are contained in this chapter.

4.2 Stylized Facts.

Sound infrastructure is imperative for growth in ECOWAS countries. Over the last decade, infrastructure improvements have boosted growth in the ECOWAS region by one percentage point per capita per year. This positive growth effect has come almost entirely from the ICT revolution, while deficient power infrastructure has held economic growth back by 0.1 percentage point per capita per year. According to Ranganthan and Foster (2019), If infrastructures in the ECOWAS region could be improved to the level of the strongest

performing country in Africa (Mauritius), regional growth performance would be boosted by some 5 percentage points.

As noted earlier, infrastructural development in the ECOWAS region ranks consistently behind these of the Southern African Development Community (SADC) on all aggregate infrastructure indicators as shown in table 4.1. There are, however, some substantial country variations within the region. This study considers infrastructure as transport (roads, rails, ports and airports) electricity and information communication technology ICT.

Table 4.1: Infrastructure in ECOWAS with other Economic Communities

	ECOWAS	EAC	SADC	CENTRAL
Paved road density	38	29	92	4
Mainline density	28	6	80	13
Mobile density	72	46	133	84
Internet Density	2	2	4	1
Generation capacity	31	16	176	47
Improved water	63	71	68	53
Sanitation	35	42	46	28

Source: Africa Infrastructure Country Data (AICD), 2023. EAC (East African Community); SADC (Southern African Development Community); and CENTRAL (Economic and Monetary Community of Central Africa.)

Transport infrastructure consists of roads, rails ports and airports. Surface transport is much slower and costlier in Africa than anywhere else in the world. Majority of the ECOWAS countries have paved their portion of regional road network except for a handful of post conflict nations. Regional road network is defined as the network needed to connect all national capitals with each other and with the major deep sea ports. Overall, 93% of this network has been paved (table 4.2). Most ECOWAS members have made the investments necessary to pave the portions of the regional network that fall within their borders. The only exception to this pattern is The

Gambia and post conflict countries such as Liberia and Sierra Leone, where a substantial share of the regional network remains unpaved (Ranganthan and Foster, 2019).

However, ECOWAS members vary substantially in the quality of their maintenance of the regional road network. Overall, 73% of the regional network is in good or fair condition (Table 4.2). As a general rule, most member countries are succeeding in maintaining their portions of the regional network in good or fair condition. However, there are five important exceptions to this pattern. Côte d'Ivoire, Senegal, Togo, Guinea, and Benin have allowed 30 to 60% of their regional networks to fall into poor condition. This may be symptomatic of wider deficiencies in the funding and implementation of road maintenance works in these countries, or it may denote a lack of prioritization to regional routes within the national road plans.

Table 4.2: ECOWAS Regional Road Condition by Member Country

	Condition %				**Type %**		
Country	**Good**	**Fair**	**Poor**	**Unknown**	**Paved**	**Unpaved**	**Unknown**
Benin	35.8	1.8	61.5	1	76.8	3.2	0.0
B/Faso	58.2	23.6	8.2	0	100.0	0.0	0.0
Ivory Coast	16.1	47.1	35.2	1	90.3	9.7	0.0
Gambia	0.0	89.4	10.6	0	47.4	34.4	18.2
Ghana	70.3	23.6	6.1	0	100.0	0.0	0.0
Guinea	22.2	20.7	57.1	0	89.1	10.9	0.0
Guinea Bissau	0.0	0.0	0.0	100	0.0	0.0	100.0
Liberia	39.4	55.9	2.7	2.1	47.5	52.5	0.0
Mali	66.6	21.7	0.0	11.7	99.6	0.4	0.0
Niger	31.2	31.0	0.0	37.7	88.0	12.0	0.0
Nigeria	55.6	29.7	14.7	0	100.0	0.0	0.0
Senegal	39.8	15.1	45.1	0.0	98.8	0.2	0.0
Sierra Leone	19.5	58.4	22.1	0.0	100.0	0.0	0.0
Togo	49.7	0.0	50.3	0.0	100.0	0.0	0.0
ECOWAS	45.1	28.4	22.5	4.0	92.5	7.4	0.1

Source: AICD various sources, 2023.

In terms of railways, regional rail network is almost absent in the ECOWAS region when compared to SADC. National rail network of ECOWAS member states are mostly disconnected from members states. Nigeria recently awarded a rail contract for a rail track to be built from Kano to Maradi in Niger Republic. The condition of the rail network in the ECOWAS region is in sharp contrast to that of SADC, where interconnected national railway systems form a regional railway network that spans half a dozen countries and extends from the south of Congo DR all the way to Durban in South Africa.

One of the factors militating against regional rail network in the ECOWAS region as Ranganathan *et al* (2019) notes is the existence of multiple rail gauges. Nigeria and Ghana uses the cape gauge (1.067 milimetres in width). Most of the francophone countries operate the metre guage (1,000 milimetres in width). Guinea and Liberia use 1,435 milimetre widths. Hopefully, with the reawakening of the rail sector in Nigeria, the rail transport infrastructure in the ECOWAS region will receive a boost. The case for further regional integration of railway networks is constrained by the relatively limited usage of existing lines. Rail traffic density in West Africa is only a fraction of that found in southern Africa and North Africa (figure 4.1).

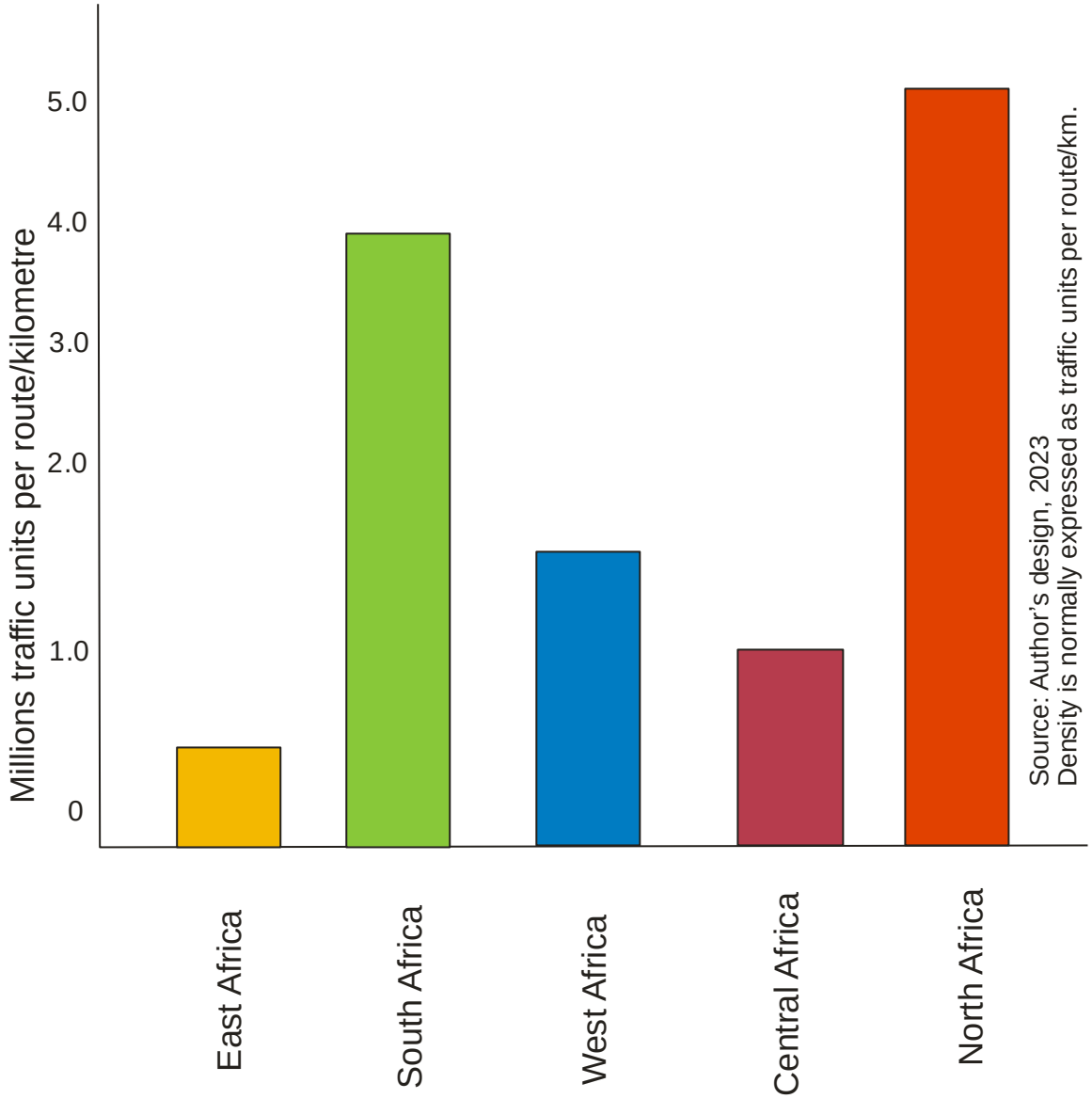
With the exception of Ghana Railways Corporation (GRC), most of ECOWAS railways are serving well under one million traffic units per year. (The Nigeria Railways Corporation could potentially serve a much higher volume of traffic than it does today, but it has suffered long-term decline due to neglect and substandard performance. The resurgence of the rail transport system in Nigeria is a welcome development. The recent attacks on passengers and vandalisation of rail tracks remain an issue.) By global standards, these levels of traffic are little more than what might be carried by a moderately busy branch line. Moreover, such low traffic volumes do not generate the revenue needed to finance track rehabilitation and upgrading. Under these market

conditions, and given the technical incompatibilities, the case for further integration of railway networks is quite limited.

Before contemplating further extensions to the rail network, a turnaround in the performance of existing railways is sorely needed to regain competitiveness with road transport. The poor quality of service provided by railways in the ECOWAS region makes it increasingly difficult for them to compete with road transportation. Most railways in the region operate at the standard at which they were originally built and now face major problems with competing modes of transport. The region's tracks can accommodate relatively lightweight and slow-moving trains. Poor maintenance over extended periods of time has caused the deterioration of many sections of the track beyond repair and resulted in a loss of competitiveness and rolling-stock productivity. While such inefficiencies can be tolerated on low-volume feeder lines and may be the only way some can be viably operated, they are a major handicap when competing against the modern roads being built in major corridors.

Rail traffic density in the ECOWAS region is only but a fraction of what is found Southern Africa and North Africa see figure 4:1 below:

Fig. 4.1: Rail Density in Africa



Container and general cargo traffic coming to the ports in the ECOWAS region has witnessed substantial increases over the years. This increase is not unconnected with the rapid economic growth in the sub-Saharan Africa region, rising global trade, ports privatization and advent of modern container vessels. These increased port activities have led to capacity constrains in the ports within the region. It was in a bid to lessen these constraints that the Federal Government of Nigeria instituted the Port Reforms as encapsulated in the Ease of Doing Business Reforms 2017

in Nigeria. The performance of the various ports in ECOWAS countries varies (see table 4.3), Ports in Nigeria and Ghana appear to perform significantly worse than others in terms of efficiency. It takes longer periods to clear containers. It is usually over a month. Meanwhile ports in Ivory Coast, Benin, Senegal, Togo, perform significantly better, in terms of efficiency. A comparative performance of ports in the ECOWAS region is presented in table 4.3 below.

Table 4.3: ECOWAS Port Performance

	Abidjan (Ivory Coast)	Apapa (Nigeria)	Catanour (Benin)	Dakar (Senegal)	Harcourt (Nigeria)	Lorne (Togo)	Tema (Ghana)
Performance							
Container dwell time (days)	12	42	12	7	30	13	25
Truck processing time (hrs)	3	6	6	5	24	4	8
Crane productivity (container per hr)	18	12	-	-	-	-	13
Crane productivity (tonnes per hr)	16	9	15	-	8	23	14
Charges							
Container handling charge 450	260	155	180	160	-	220	768
General Cargo handling	14	8	9	15	9	9	10

Source: AICD Ports data base 2023

ECOWAS's air transport appears to be the most liberalized in Africa. The region has achieved progress in instituting free pricing, lifting capacity and frequency restraints and allowing airlines to fly so-called-fifth-freedom routes. This feat is yet to be achieved by the eastern and southern Africa region. Only very few countries within the region have made appreciable progress towards achieving international standards in air safety – Nigeria, Ghana, Senegal and Ivory Coast. The remaining ECOWAS countries are in need of significant development. Only Nigeria

and Ghana are equipped with air traffic control and weather information. There is need for maintenance and additional capacity in the existing airports. Ranganathan *et al* (2019) emphasizes the need for a central air transport hub in the ECOWAS region that can lift aircraft load factors for regional travels toward sustainable levels, thus bringing about significant benefits by increasing the frequency of service to countries with very little traffic. In terms of charges, airport charges in the ECOWAS region are high by international standards. This is as a result of their operating cost. In Nigeria recently the astronomical rise in the cost of aviation fuel has driven the cost of air travels above board. This of course has its attendant effects.

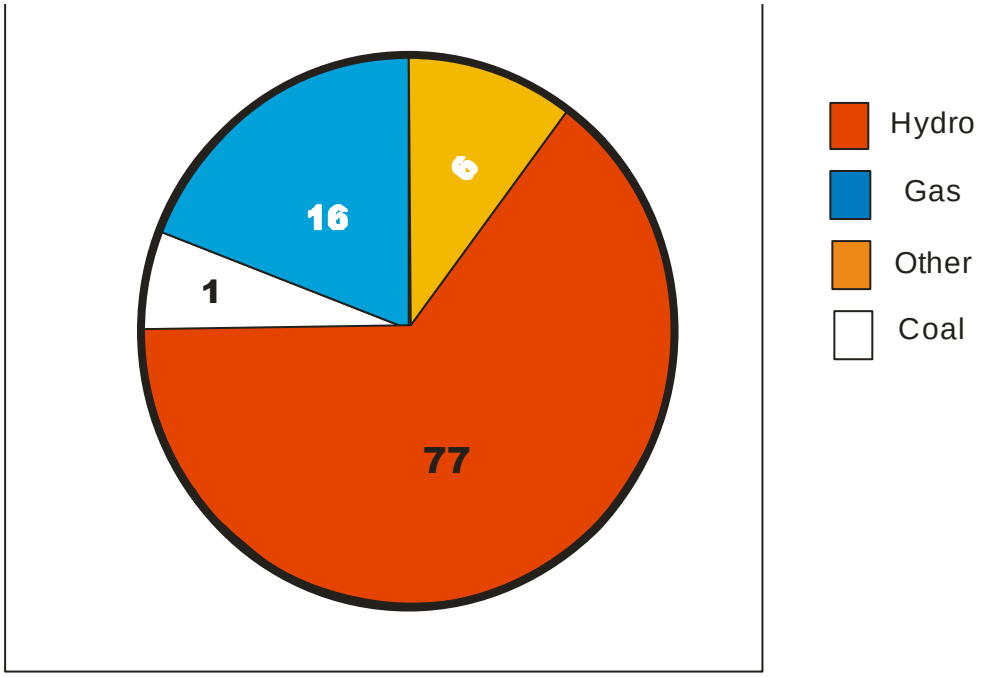
According to Ranganathan *et al* (2019), ECOWAS region is relatively ahead in terms of electrification but is lagging behind in terms of generation capacity, service reliability and utility performance. Access to electric power stands at 4 percent in the region which is higher than that in other sub-regions (see table 4.4 below). Availability of power is low. Power supply is very unreliable. Power outage in the region and indeed across Africa has led to private sector investments in backstop generation. Overall performance of ECOWAS power utilities leaves plenty room for improvement. On a positive note, the ECOWAS power utilities have the best record of cost recovery of any of the regional blocks in Africa, with power tariffs covering 79 percent of full capital cost of service provision.

Table 4.4: Power Performance in Africa

	ECOWAS	CEMAC	EAC	SADC	COMESA
Installed generation capacity (mw)	16,912	2,072	3,211	42,814	4,800
Net generation per capita, annual (kwh/capita hr)	291	186	112	1892	162
Outages, number, annually (number/year)	212	209	166	91	196
Outages value lest annually (% of sales)	14	10	16	4	14
Firms with own generator (% of firms)	57	51	54	19	43
Access (Urban, % of population)	50	31	23	35	34
Growth in access of population to electricity	2	1	1	1	1
System losses (% of generation)	29	31	23	12	32
Cost recovery ratio (%)	79	45	69	68	73
Total hidden costs of revenue (%)	159	107	65	4	102
Collection rate reported by utility, Electricity (% of billing)	71	93	94	89	93

Source: Author, 2023. Note: CEMEC- Economic and Monetary Community of Central Africa; COMESA- Common Market for Eastern and Southern Africa; EAC – East African Community; SADC- Southern African Development Community.

In the ECOWAS region, Nigeria is by far the largest power producer and consumer. She accounts for about 53 percent of power consumption in the region. Nigeria is the supplier of power to Niger. Clearly, Nigeria has comparative advantage in meeting its own domestic power needs through its own hydropower and domestic power and natural gas resources. About 77 percent of electricity generation in the ECOWAS region is hydro powered. Natural gas accounts for 16 percent. The remaining 7 percent are from coal and other sources. See fig 4.2 below:



Source: AICD various sources, 2023.

Fig. 4.2 Power Generation Mix

In comparison with other regional communities in Africa, ECOWAS performs better in terms of access to information and communication technology but faces relatively high prices for critical ICT services with an international band width at over 16 bits per capita and mobile subscriptions at well over 25 per 100 inhabitants, the region ranks next to SADC. An overview of broadband access rates and internet subscriptions in the continent shows ECOWAS is behind SADC. This may be attributable to higher tariffs in the ECOWAS region. Prices of international telephone cells and fixed-line telephone service are however low. See Table 4.5 below.

Table 4.5 ICT infrastructure across Regional Community

	ECOWAS	CEMAC	EAC	SADC	COMESA
Breadband Subscribers (per inhabitant 100)	0.15	0.05	0.20	0.12	1.80
International internet bandwidth (per capita)	64	44	36	43	76
Internet subscribers (per 100 inhabitants)	0.96	0.34	0.36	0.25	1.59
Mainlines outside largest cities (per 100 inhabitants)	1.56	0.80	2.12	0.96	7.56
Mobile telephone subscribers (per 100 inhabitants)	75	62	47	37	87
Prepaid mobile price basket (USD per month)	84	57	36.9	41	44.6
Price of fixed telephone price (USD/Month)	36.3	41.7	28.6	46.3	47.1

Source: Author's Compilation 2023.

Broadly, speaking, ICT access and prices vary among countries in the region. Within the ECOWAS region, there are two groups: The first group comprises of countries with relatively high mobility penetration (generally in excess of 30 subscribers per 100 population), mobile footprint (excess of 70 percent of the population and international bandwidth (above 40 bits per capita) – Nigeria, Ghana, Senegal, Ivory Coast and Cape Verde. The second group which is made up of the remaining ECOWAS countries has some largely poor indicators across board-below 20 mobile penetrations, mobile footprint generally below 60 percent of the population and international bandwidth below 20 bits per capita. The ICT subsector in the region has got great potentials. Nigeria with her population and a youthful ICT compliant population is a destination for ICT investments. Billions of dollars investments are needed to address ICT gaps within the region.

4.3 Descriptive Statistics

The descriptive statistics of the selected variables are shown in the table below:

Table 4.6: Descriptive Statistics of the Variables in the Models.

	AGRMAF_GDP	AGR_GDP	MAF_GDP	EMPLOY_AGR	EMPLOY_MAF	ELECTinfra	TRANSinfr	ICTinfra	WATERinfra	AGRICinfra	CU	FDI	FSD
Mean	38.24584	29.27082	8.975022	49.29491	15.33983	36.66574	2.220671	204.2548	4.872121	45.48537	3.12E+09	4.659888	15.91325
Median	37.01450	26.45647	8.680379	47.30500	12.02500	33.56191	2.264531	49.27120	4.666091	46.07074	7.10E+08	2.432675	12.96014
Maximum	80.91544	79.04236	21.49191	89.57000	67.60000	95.81540	2.890000	49965.00	16.27645	76.25421	6.44E+10	103.3374	73.90753
Minimum	11.27042	4.632906	1.532609	10.56000	5.420000	1.200000	1.400000	0.000000	0.236957	14.63206	16871300	-2.544539	0.000000
Std. Dev.	11.87296	13.46874	4.360915	16.53487	13.19549	22.40961	0.258557	2747.895	3.802085	17.30017	8.74E+09	10.08475	12.94192
Skewness	0.551107	0.953409	0.369893	-0.119254	2.755596	0.491900	-0.281285	18.07667	0.557336	-0.043278	4.560362	7.057377	2.205579
Kurtosis	4.295891	4.190858	2.741119	2.305595	10.01942	2.400330	3.102540	327.8455	2.526944	1.857982	24.92513	59.11301	8.670692
Jarque-Bera	39.79536	69.49382	8.446662	7.412417	1095.126	18.25266	4.496246	1468935.	20.16126	18.03582	7753.610	46033.57	709.7071
Probability	0.000000	0.000000	0.014650	0.024571	0.000000	0.000109	0.105597	0.000000	0.000042	0.000121	0.000000	0.000000	0.000000
Sum	12621.13	9659.369	2961.757	16267.32	5062.144	12099.69	732.8214	67404.07	1607.800	15010.17	1.03E+12	1537.763	5251.371
Sum Sq. Dev.	46378.23	59682.93	6256.782	89949.20	57285.77	165220.7	21.99420	2.48E+09	4755.975	98468.34	2.52E+22	33459.99	55105.33
Observations	330	330	330	330	330	330	330	330	330	330	330	330	330

Source: Authors' computation using e-views 9.0, 2023

The real sector performance was captured by the real sector value added as a percentage of total GDP. From the statistics, the maximum value was 80.91% with a minimum value of 11.27%. The mean value was 38.24% for the ECOWAS countries during the period under review. This implies that the real sector value added as a percentage of GDP was 38.24% for the 15 ECOWAS during the review period. The agricultural sector value added as a percentage of total GDP shows a maximum value of 79.04% and a minimum value of 4.63%. On the average, the agricultural sector value added as a percentage of total GDP was 29.27% for the fifteen ECOWAS countries during the period under review.

The manufacturing sector value added as a percentage of total GDP shows a maximum value of 21.49% and a minimum value of 1.53%. On the average, the manufacturing sector value added as a percentage of total GDP was 8.97% for the fifteen ECOWAS countries during the period under review. Comparing this with the agricultural sector value added, it shows clearly that ECOWAS countries are more into agriculture relative to manufacturing.

In terms of employment in the agricultural and manufacturing sectors, agricultural sector generated more employment than the manufacturing sector in ECOWAS countries during the period 2000 – 2021. From the statistics, agricultural sector employed a maximum of 87.57% to the total labour force with a minimum of 10.56% during the period under review. Manufacturing sector on the other hand, has a maximum figure of 67.6% and minimum of 5.42%. On the average, employment in the agricultural sector was 49.29% while the manufacturing sector employed 15% of the labour force during the period under review.

Infrastructural development was captured using five indicators. These included electricity infrastructure which use percentage of population with access to electricity as proxy, transportation infrastructure using transportation composite index as proxy, ICT infrastructure

using mobile cellular subscription per 100 people as proxy, water infrastructure using volume of water available for irrigation as proxy and agricultural infrastructure using agricultural land as a percentage of total land area as proxy.

From the statistics, electricity has a maximum value of 95.81% and a minimum of 12%. On the whole, an average of about 36.33% of the total population of ECOWAS states has access to electricity during the period under review. This is a clear indication of the poor level of electricity infrastructure in ECOWAS states.

Transportation infrastructure has maximum and minimum values of 2.89 and 1.4 respectively. The average transportation composite index was 2.23 for the sub-region during the period under review. The statistics for ICT infrastructure shows some good performances. The maximum and minimum cellular subscription per 100 people for the sub-region was 49,965 and 0.00 respectively. On the average, ECOWAS countries have 204.25 mobile cellular subscriptions per 100 people during the period under review.

Statistics on water infrastructure shows the maximum volume of water for irrigation during the period under review was 16.27 while the minimum volume was 0.23. On the average, the amount of water available for irrigation in ECOWAS countries during the period under review was 4.87. Similarly, Agricultural infrastructure shows a maximum value of 76.25% while the minimum was 14.63%. The mean land available for agriculture during the period under review was 45.48% for ECOWAS countries.

The descriptive statistics further revealed that all the variables except transportation infrastructure were not normally distributed. This can be clearly seen from the coefficients of skewness and kurtosis and also summarized by the Jarque – Bera statistics. From the probability

value of the Jarque – Bera statistics, all the variables have values less than 0.05 except transportation infrastructure with a probability value of 0.1055. This could have been caused by the heterogeneity issues normally associated with panel data analysis, as the constituting units are not normally homogenous. This justified the use of GMM technique which yield consistent results even in this circumstance provided the moment conditions are met.

4.4 Time Series Properties of the Variables of the Model.

The examination of time series properties of variable used for the analysis involve panel unit root test and panel co-integration test. The unit root test asses the stationarity status of the individual variables, while the co-integration test is a group statistics accessing the long run relationship status of the group of variables used in the analysis.

4.4.1 Panel Unit Root Test

In testing for unit root in the series in the model, the Levin, Lin and Chu test was employed. The Levin, Lin and Chu test assumes common unit root process. The results are presented in the tables 4.7 and 4.8 below:

Table 4.7: Panel Unit Root Test for Variables in Level.

Variables	Levin. Lin & Chu test	
	Statistic	**P-value**
$AGRMAF_GDP$	-1.7212	0.0626
AGR_GDP	-1.4078	0.0796
MAF_GDP	-2.7086	0.0034*
$EMPLOY_AGR$	-1.1741	0.2108
$EMPLOY_MAF$	-1.8478	0.0623
$ELECTinfra$	-0.9875	0.1617
$TRANSinfra$	-0.3386	0.3675
$ICTinfra$	-1.8353	0.0632
$WATERinfra$	-5.5082	0.0000*
$AGRICinfra$	-3.2677	0.0005*
CU	-0.6798	0.2483
FDI	-1.5808	0.0470*
FSD	-1.2479	0.1066

Source: Authors' computation using e-views 9.0, 2023 *significant at 5%

The result in table 4.7 above shows unit root results for unit root test for variables in levels tested at 5% level of significance. From the table, all variables have unit root except manufacturing sector output, water infrastructure and Agriculture infrastructure and Foreign Direct Investment (FDI). This implies that these variables are integrated of order zero {I(0)}. Other variables that were not stationary in levels were tested for unit root at first order difference. The result is presented in table 4.8 below:

Table 4.8: Panel Unit Root Test for Variables in First Order Difference

Variables	Levin. Lin & Chu test	
	Statistic	**P-value**
DAGRMAF_GDP	-10.0738	0.0000*
DAGR_GDP	-13.2636	0.0000*
DEMPLOY_AGR	5.0413	0.0012*
DEMPLOY_MAF	2.7602	0.0065*
DELECTinfra	-8.9450	0.0000*
DTRANSinfra	-7.3985	0.0000*
DICTinfra	-2.8599	0.0021*
DCU	-11.1533	0.0000*
DFSD	-6.1502	0.0000*

Source: Authors' computation using e-views 9.0, 2023 *significant at 5%

From the result in table 4.8, the entire variables are stationary at 5% level of significance. This implies that real sector performance variable, Agricultural sector output, Agricultural sector employment, manufacturing sector employment, electricity infrastructure, transport infrastructure, ICT infrastructure, capacity utilization and financial sector development are stationary in first order difference and hence, they are said to be integrated of order one {I(1)}.

4.4.2 Panel Co-integration Test:

Since some variables were not stationary in level, there was need to conduct a co-integration test to ascertain if there exist a long run relationship among the variables. Given that the analysis is based on panel data, the Pedroni Residual Co-integration Test was adopted. Pedroni Residual Co-integration test introduced in 1999 by Peter Louis Pedroni consist of seven test statistics that test the null hypothesis of no co-integration in non-stationary panels. The seven test statistics allow heterogeneity in the panel, both in the short-run dynamics as well as in the long-run slope and intercept coefficients. Also, the test is valid even when the series are integrated of different

orders. The result of the test is presented in the tables 4.9a and 4.9b below at 5% level of significance.

Table 4.9a: Pedroni Residual Co-integration Test (Within Dimension)

	Statistics	**Probability**	**Weighted Statistics**	**Probability**
Panel v-statistics	3.275761	0.0014	-4.292277	0.0000
Panel rho-Statistic	3.910738	0.0001	4.705448	0.0000
Panel PP-Statistic	-3.925181	0.0000	-5.253938	0.0000
Panel ADF-Statistic	-5.841543	0.0000	-4.704920	0.0000

Source: Authors' computation using e-views 9.0, 2023

Table 4.9b: Pedroni Residual Co-integration Test (Between Dimensions)

	Statistics	Probability
Group rho-Statistic	3.643187	0.0001
Group PP-Statistic	-6.707238	0.0000
Group ADF-Statistic	-3.581836	0.0002

Source: Authors' computation using e-views 9.0, 2023

The Pedroni Residual Co-integration Test consists of seven test statistics. The first four statistics which are panel v-statistics, rho-statistics, Philips – Perron statistics and ADF statistics were computed using common autoregressive coefficient (within-dimension). The other three statistics employed individual autoregressive coefficient (between-dimension). The probability value of all the statistics were less than 0.05. This clearly shows that the variables are co-integrated. Given that the variables are co-integrated, it is safe to proceed to compute the short run and long run coefficients of the variables.

4.5 Estimation Results

The specified model was estimated using the Generalized Method of Moment (GMM). The generalized method of moments (GMM) is a statistical method that combines observed economic data with the information in population moment conditions to produce estimates of the unknown parameters of the economic model.

The GMM method is highly justified for panel data analysis as it helps to eliminate endogeneity problem that is common with panel data. Generally, endogeneity which arises from three main sources (unobserved heterogeneity, simultaneity and dynamic endogeneity) leads to inconsistent estimates. The GMM helps to eliminate the endogeneity issue by internally transforming the data. Once the moment conditions are met, GMM yield consistent results.

The GMM which is a class of Instrumental Variable (IV) technique depends on the use of appropriate instruments for the moment condition to be met. In this analysis, internal instrument which involve the use of the lagged values of the explanatory variables was employed. One of the very important statistics is the J-statistic, which is a test of over identification restrictions. In other words, it is used to test for the validity of the instruments. The results from the GMM estimation are presented below in tables 4.10a, 4.12, 4.13a, 4.15, 4.16a, 4.18, 4.19a, 4.21, 4.22a, 4.24.

4. 5.1a Model 1: Real Sector Performance Model - Short run Coefficients of Variables

The estimation result of the real sector output model which shows the short run coefficients of variables is presented in table 4.10 below:

Table 4.10a: Short run Coefficients of the Variables in the Real Sector Performance Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AGRMAF_GDP(-1)	0.247686	0.107926	2.294961	0.0015
$EMPLOY_AGR$	6.164643	2.451131	2.515019*	0.0012
$EMPLOY_MAF$	3.990856	1.106170	3.607814*	0.0000
$ELECTinfra$	0.299216	0.821672	0.364155	0.7160
$TRANSinfra$	14.40374	53.00420	0.271747	0.7860
$ICTinfra$	0.000575	0.000732	0.785582	0.4328
$WATERinfra$	8.768990	27.09795	0.323603	0.7465
$AGRICinfra$	0.073278	1.302165	0.056274	0.9552
CU	-0.005577	0.002162	-2.579555*	0.0009
FDI	0.155576	0.487005	0.319455	0.7496
FSD	1.859841	3.824527	0.486293	0.6271

Source: Authors' computation using e-views 9.0, 2023

Table 4.10b: J-Statistics

J-statistic	5.024286
Prob(J-statistic)	0.284815

Source: Authors' computation using e-views 9.0, 2023

From the above result, the J-statistics has a coefficient of 5.0242 and a probability value of 0.2848. Since the probability value is greater than 0.05, the null hypothesis which states that the instruments are not valid is rejected. This implies that the instruments are valid and hence the results are consistent.

The sign expectations for all the variables are met except for capacity utilization CU which shows a negative sign. Hence all the selected variables have positive impact on real sector output except capacity utilization. However, using the t-ratio to judge the significance of the impact of the explanatory variables, the result shows that none of the variables used to capture infrastructural development were significant even at 10% level. This clearly implies that the impact of infrastructural development on real sector output is not statistically significant in the short run.

From the result also, the impact of the lagged value of the real sector output (AGRMAF_GDP-1), employment in the agricultural sector ($EMPLOY_AGR$), employment in the manufacturing sector ($EMPLOY_MAF$) and capacity utilizations (CU) on $AGRMAF_GDP$ was statistically significant at 1% level. The impact of electricity infrastructure ($ELECTinfra$), transportation infrastructure ($TRANSinfra$), ICT infrastructure ($ICTinfra$), water infrastructure ($WATERinfra$), agriculture infrastructure ($AGRICinfra$), foreign direct investment (FDI) and financial sector development (FSD) on real sector output ($AGRMAF_GDP$) though positive were not statistically significant even at 10% level. The key diagnostic test available for GMM using e-views are serial correlation test and normality tests. The existence of serial correlation among the residuals was tested using Arellano-Bond serial correlation test. The result is presented in the table below:

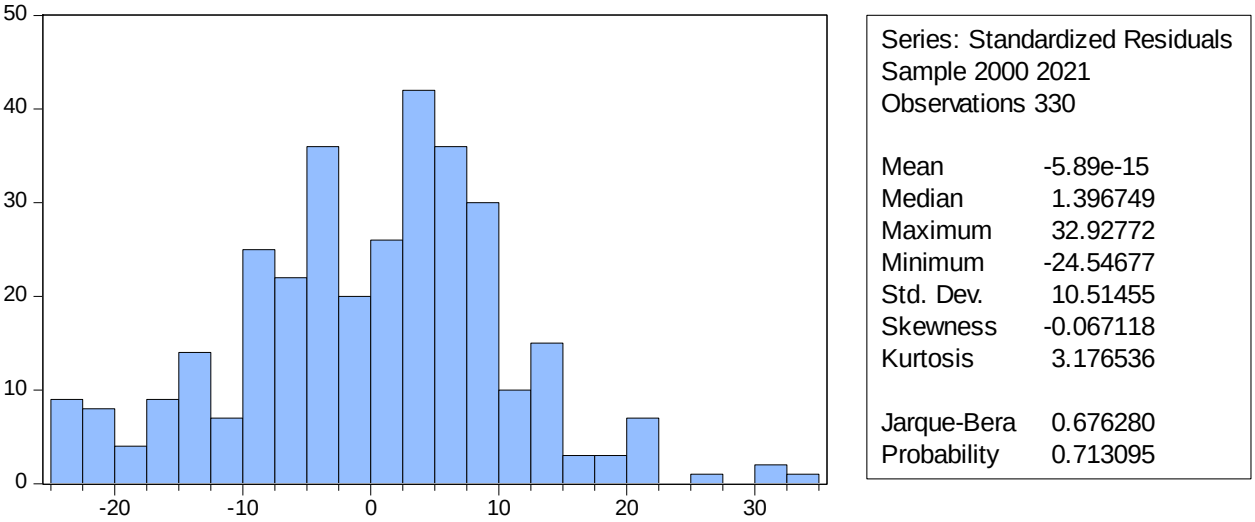
Table 4.11: Arellano-Bond Serial Correlation Test

Test Order	m-Statistic	rho	SE(rho)	Prob.
AR(1)	0.050015	4048.369064	80943.65062	0.9601
AR(2)	0.024103	2443.342369	101369.9067	0.9808

Source: Authors' computation using e-views 9.0, 2023

From the above result, the probability values of AR(1) and AR(2) are 0.9601 and 0.9808 respectively. Since these values are greater than 0.05, the null hypothesis of the existence of serial correlation is rejected against the alternative hypothesis. Hence it can be concluded that there is no serial correlation among the error terms in the model. The normality of the residual distribution was tested for using histogram. The result is presented below:

Figure 4.3



Source: Authors' computation using e-views 9.0, 2023

From the result, the skewness coefficient was -0.067118 with kurtosis of 3.1765. This shows a normal distribution with a standard normal kurtosis. The overall test for normality is shown by the Jarque-Bera statistics. The Jarque-Bera has a coefficient of 0.6762 with a probability of 0.7130. Since the probability value is greater than 0.05, it can be concluded that the residual is normally distributed.

4. 5.1b Model 1: Real Sector Performance Model – Long run Coefficients of Variables

Given the good performance of the diagnostic test, it is safe to proceed to compute the long run coefficient which is most useful for policy simulation. The coefficients of variables are shown in the table below.

Table 4.12: Long run Coefficients for Variables in Real Sector Performance Model

Variables	Coefficients	t – Statistics	P – Value
$EMPLOY_AGR$	0.4175	2.4322*	0.0008
$EMPLOY_MAF$	0.2913	1.9017**	0.0113
$ELECTinfra$	2.9058	2.5340*	0.0000
$TRANSinfra$	0.9678	2.8933*	0.0000
$ICTinfra$	2.3862	7.8637*	0.0000
$WATERinfra$	0.0674	0.5440	0.5869
CU	4.2437	0.5061	0.6132
FDI	0.1563	3.8033*	0.0000
FSD	0.0671	2.7955*	0.0000

* = significant at 1% **= significant at 5%

Source: Authors computation using e-views 9.0, 2023.

From the above result, all variable have correct sign and the test statistics shows good performance. The impact of all the explanatory variables on the dependent variable was statistically significant except for water infrastructure ($WATERinfra$) and capacity utilization (CU).

Employment in agricultural sector ($EMPLOY_AGR$) has a coefficient of 0.4175 with a t-statistics of 2.4322 and a corresponding p-value of 0.0008. This shows that an increase in employment in agricultural sector by one unit will lead to an increase in real sector output by 0.4175%. This impact was statistically significant at 1% level.

Employment in manufacturing sector ($EMPLOY_MAF$) has a coefficient of 0.2913 with a t-statistics of 1.9017 and a corresponding p-value of 0.0113. This shows that an increase in employment in manufacturing sector by one unit will lead to an increase in $AGRMAF_GDP$ by 0.2913%. This impact was statistically significant at 5% level.

Electricity infrastructure ($ELECTinfra$) has a coefficient of 2.9058 and a t-ratio of 2.5340 and a corresponding p-value of 0.0000. This shows that an increase in electricity infrastructure by one

unit will lead to increase in $AGRMAF_GDP$ by 2.9058%. This was statistically significant at 1% level.

Transportation infrastructure ($TRANSinfra$) has a coefficient of 0.9678 and a t-ratio of 2.8933 and a corresponding p-value of 0.0000. This shows that an increase in Transportation infrastructure by one unit will lead to $AGRMAF_GDP$ by 0.9678%. This was statistically significant at 1% level.

ICT infrastructure ($ICTinfra$) has a coefficient of 2.3862 and a t-ratio of 7.8637 and a corresponding p-value of 0.0000. This shows that an increase in ICT infrastructure by one unit will lead to $AGRMAF_GDP$ by 2.3862%. This was statistically significant at 1% level.

Foreign Direct Investment (FDI) has a coefficient of 0.1563 and a t-ratio of 3.8033 and a corresponding p-value of 0.0000. This shows that an increase in FDI by one unit will lead to increase in $AGRMAF_GDP$ by 0.1563%. This was statistically significant at 1% level.

Similarly, Financial Sector Development (FSD) has a coefficient of 0.0671 and a t-ratio of 2.7955 and a corresponding p-value of 0.0000. This shows that an increase in Financial Sector Development by one unit will lead to increase in $AGRMAF_GDP$ by 0.0671%. This was statistically significant at 1% level.

The impact of water infrastructure ($WATERinfra$)) and capacity utilization (CU) on $AGRMAF_GDP$ though positive were not significantly different from zero.

4. 5. 2a Model 2: Agricultural Sector Performance Model: Short run Coefficients of Variables

The estimation result of the agricultural sector output model which shows the short run coefficients of variables is presented in the table below

Table 4.13a: Short run coefficients of variable in the agricultural sector performance model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AGR_GDP(-1)	0.918288	0.191290	4.800509*	0.0000
(*EMPLOY_AGR*)	2.671961	2.777490	0.962006	0.3369
ELECTinfra	0.208691	0.374669	0.557003	0.5780
TRANSinfra	2.477727	13.81114	0.179401	0.8578
ICTinfra	0.000399	0.000548	0.728376	0.4670
WATERinfra	14.38526	9.998033	1.438809	0.1513
AGRICinfra	0.431065	0.919026	0.469046	0.6394
CU	4.03E-11	5.18E-10	0.077867	0.9380
FDI	-0.254219	0.219949	-1.155809	0.2488
FSD	0.898468	1.935726	0.464151	0.6429

Source: Authors' computation using e-views 9.0, 2023

Table 4.13b: J-Statistics

J-statistic	5.180905
Prob(J-statistic)	0.394204

Source: Authors' computation using e-views 9.0, 2023

From the above result, the J-statistics has a coefficient of 5.1809 and a probability value of 0.3942. Since the probability value is greater than 0.05, the null hypothesis which states that the instruments are not valid is rejected. This implies that the instruments are valid and hence the results are consistent.

The sign expectations for all the variables are met except for FDI which show a negative sign. Hence all the selected variables have positive impact on real sector output except FDI. However, using the t-ratio to judge the significance of the impact of the explanatory variables, the result

shows that none of the variables used to capture infrastructural development was significant even at 10% level. This clearly implies that the impact of infrastructural development on agricultural sector output is not statistically significant in the short run. Also, from the result, only the impact of the lagged value of agricultural out was statistically significant at 1% level. Other variables were not statistically significant even at 10% level. The key diagnostic test available for GMM using e-views are serial correlation test and normality tests. The existence of serial correlation among the residuals was tested using Arellano-Bond serial correlation test. The result is presented in the table below:

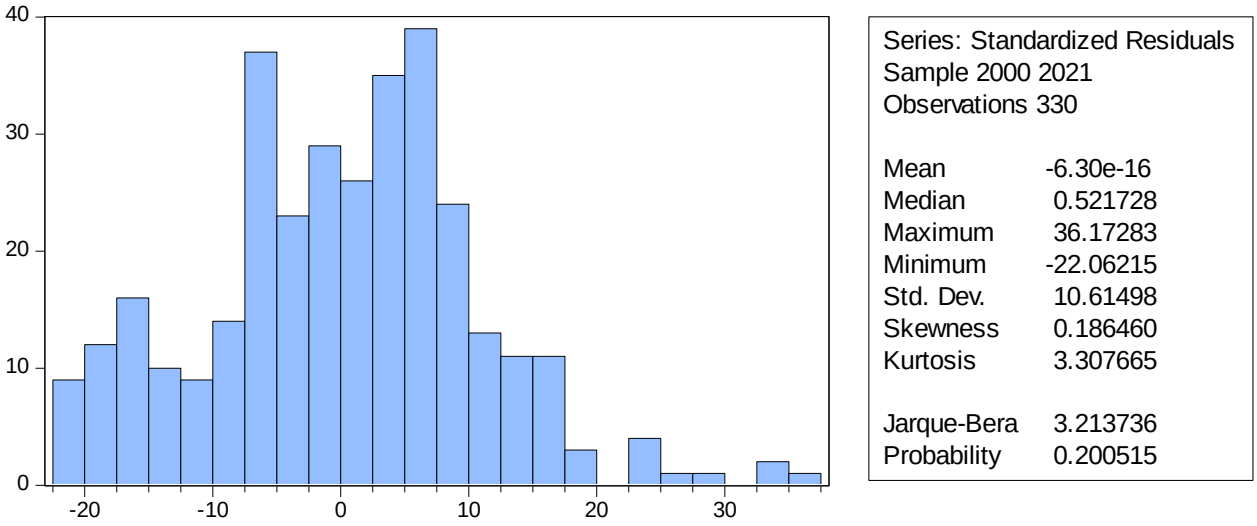
Table 4.14: Arellano-Bond Serial Correlation Test

Test Order	m-Statistic	rho	SE(rho)	Prob.
AR(1)	-0.311274	-85.498058	274.671619	0.7556
AR(2)	-1.281690	-524.858262	409.504695	0.2000

Source: Authors' computation using e-views 9.0, 2023

From the above result, the probability values of AR(1) and AR(2) are 0.7556 and 0.2000 respectively. Since these values are greater than 0.05, the null hypothesis of the existence of serial correlation is rejected against the alternative hypothesis. Hence it can be concluded that there is no serial correlation among the error terms in the model. The normality of the residual distribution was tested for using histogram. The result is presented below:

Figure 4.4



Source: Authors' computation using e-views 9.0, 2023

From the result, the skewness coefficient was 0.1864 with kurtosis of 3.3076. This shows a normal distribution with a standard normal kurtosis. The overall test for normality is shown by the Jarque-Bera statistics. The Jarque-Bera has a coefficient of 3.2137 with a probability of 0.2005. Since the probability value is greater than 0.05, it can be concluded that the residual is normally distributed.

4. 5. 2b Model 2: Agricultural Sector Performance Model: Long run Coefficients of Variables

Given the good performance of the diagnostic test, it is safe to proceed to compute the long run coefficient which is most useful for policy simulation. The coefficients of variables are shown in the table below.

Table 4.15: Long run Coefficients for Variables in Agricultural Performance Output Model

Variables	Coefficients	t – Statistics	P – Value
$(EMPLOY_AGR)$	3.2211**	1.9927**	0.0439
$ELECTinfra$	0.9684*	3.8662*	0.0001
$TRANSinfra$	2.7417*	12.7679*	0.0000
$ICTinfra$	0.9183*	4.8027*	0.0000
$WATERinfra$	14.4538*	9.9564*	0.0000
$AGRICinfra$	1.1829***	1.8914***	0.0674
CU	0.9182*	4.8005*	0.0000
FDI	0.9863*	4.6766*	0.0000
FSD	-8.1458	-0.0474	0.9622

* = significant at 1% **= significant at 5% ***=significant at 10%

Source: Authors' computation using e-views 9.0, 2023

From the above result, all the variables have correct sign except financial sector development (FSD). Also, the impact of all the explanatory variables on the dependent variable was statistically significant except for financial sector development (FSD).

Employment in agricultural sector ($EMPLOY_AGR$) has a coefficient of 3.2211 with a t-statistics of 1.9927 and a corresponding p-value of 0.0439. This shows that an increase in employment in agricultural sector by one unit will lead to an increase in agricultural sector output by 3.2211%. This impact was statistically significant at 5% level.

Electricity infrastructure ($ELECTinfra$) has a coefficient of 0.9684 and a t-ratio of 3.8662 and a corresponding p-value of 0.0001. This shows that an increase in electricity infrastructure by one unit will lead to increase in agricultural sector output by 0.9684%. This was statistically significant at 1% level.

Transportation infrastructure ($TRANSinfra$) has a coefficient of 2.7417 and a t-ratio of 12.7679 and a corresponding p-value of 0.0000. This shows that an increase in Transportation

infrastructure by one unit will lead to increase in agricultural sector output by 2.7417%. This was statistically significant at 1% level.

ICT infrastructure ($ICTinfra$) has a coefficient of 0.9183 and a t-ratio of 4.8027 and a corresponding p-value of 0.0000. This shows that an increase in ICT infrastructure by one unit will lead to increase in agricultural sector output by 0.9183%. This was statistically significant at 1% level.

Water infrastructure ($WATERinfra$)) has a coefficient of 14.4538 and a t-ratio of 9.9504 and a corresponding p-value of 0.0000. This shows that an increase in water infrastructure by one unit will lead to increase in agricultural sector output by 14.4538%. This was statistically significant at 1% level.

Agricultural infrastructure ($AGRICinfra$) has a coefficient of 1.1829 and a t-ratio of 1.8914 and a corresponding p-value of 0.0674. This shows that an increase in agricultural infrastructure by one unit will lead to increase in agricultural sector output by 1.1829%. This was statistically significant at 10% level.

Capacity utilization (CU) has a coefficient of 0.9182 and a t-ratio of 4.8005 and a corresponding p-value of 0.0000. This shows that an increase in capacity utilization by one unit will lead to increase in agricultural sector output by 0.9182%. This was statistically significant at 1% level.

Foreign Direct Investment (FDI) has a coefficient of 0.9863 and a t-ratio of 4.6766 and a corresponding p-value of 0.0000. This shows that an increase in FDI by one unit will lead to increase in agricultural sector output by 0.9863%. This was statistically significant at 1% level.

The impact of financial sector development on agricultural sector output was negative and also not significantly different from zero.

4. 5.3a Model 3: Agricultural Sector Employment Model - Short Run Coefficients of Variables

The estimation result of the agricultural sector employment model which shows the short run coefficients of variables is presented in the table below:

Table 4.16a: Short Run Coefficients for Variables in the Agricultural Sector Employment Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMPLOY_AGR(-1)	0.792171	0.222242	3.564456*	0.0004
$ELECTinfra$	0.014071	0.029475	-0.477377	0.6335
$TRANSinfra$	1.127133	1.424247	-0.791389	0.4294
$ICTinfra$	4.11E-05	4.21E-05	0.975773	0.3300
$WATERinfra$	0.064126	0.482003	-0.133041	0.8943
$AGRICinfra$	0.075371	0.078853	-0.955841	0.3400
CU	3.71E-10	3.89E-10	-0.954106	0.3409
FDI	-0.032232	0.032893	-0.979899	0.3280
FSD	0.020810	0.094697	-0.219748	0.8262

Source: Authors' computation using e-views 9.0, 2023. *significant at 1% level of significance.

Table 4.13b: J-Statistics

J-statistic	9.944444
Prob(J-statistic)	0.061165

Source: Authors' computation using e-views 9.0, 2023

From the above result, the J-statistics has a coefficient of 9.9444 and a probability value of 0.0611. Since the probability value is greater than 0.05, the null hypothesis which states that the instruments are not valid is rejected. This implies that the instruments are valid and hence the results are consistent.

The sign expectations for all the variables were met except for FDI which show a negative sign. Hence all the selected variables have positive impact on real sector output except FDI. However, using the t-ratio to judge the significance of the impact of the explanatory variables, the result shows that none of the variables used to capture infrastructural development was significant even at 10% level. This clearly implies that the impact of infrastructural development on agricultural sector employment is not statistically significant in the short run. Also, from the result, only the

impact of the lagged value of agricultural sector employment was statistically significant at 1% level. Other variables were not statistically significant even at 10% level. The existence of serial correlation among the residuals was tested using Arellano-Bond serial correlation test. The result is presented in the table below:

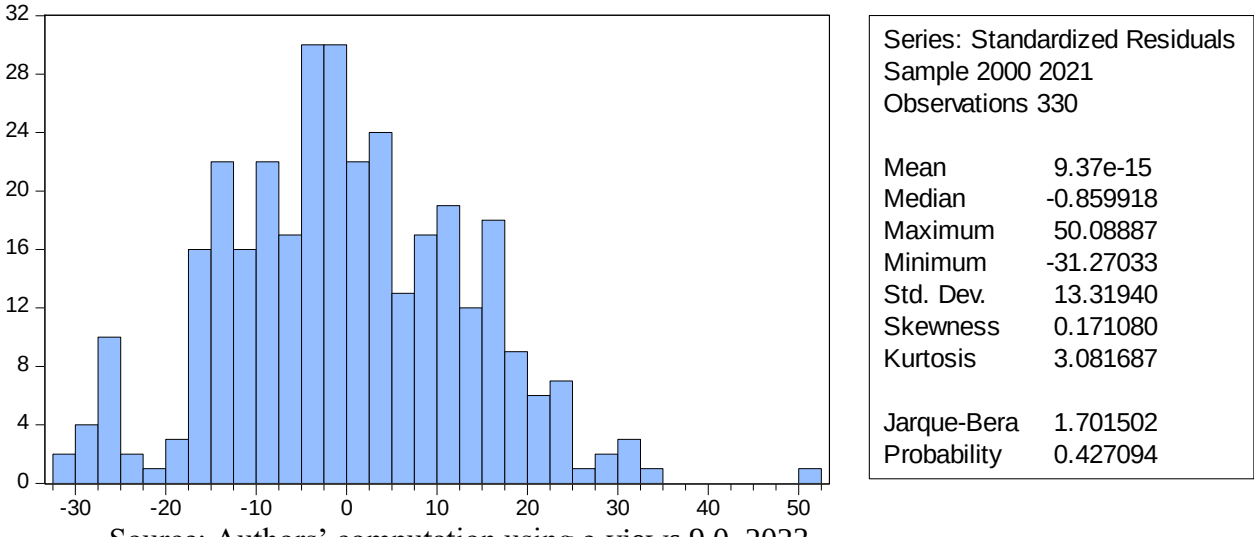
Table 4.17: Arellano-Bond Serial Correlation Test

Test order	m-Statistic	rho	SE(rho)	Prob.
AR(1)	1.058181	96.816873	138.910605	0.3902
AR(2)	0.742424	47.088230	153.634392	0.2061

Source: Authors computation using e-views 9.0, 2023

From the above result, the probability values of AR(1) and AR(2) are 0.3902 and 0.2061 respectively. Since these values are greater than 0.05, the null hypothesis of the existence of serial correlation is rejected against the alternative hypothesis. Hence it can be concluded that there is no serial correlation among the error terms in the model. The normality of the residual distribution was tested for using histogram. The result is presented below:

Figure 4.5



Source: Authors' computation using e-views 9.0, 2023

From the result, the skewness coefficient was 0.01710 with kurtosis of 3.0816. This shows a normal distribution with a standard normal kurtosis. The overall test for normality is shown by the Jarque-Bera statistics. The Jarque-Bera has a coefficient of 1.7015 with a probability of 0.4270. Since the probability value is greater than 0.05, it can be concluded that the residual is normally distributed

4. 5.3b Model 3: Agricultural Sector Employment Model – Long Run Coefficients of Variables

Given the good performance of the diagnostic test, it is safe to proceed to compute the long run coefficient which is most useful for policy simulation. The coefficients of variables are shown in the table below:

Table 4.18: Long run Coefficients for Variables in Agricultural Sector Employment Model

Variables	Coefficients	t – Statistics	P – Value
$ELECTinfra$	0.7952	3.7140*	0.0002
$TRANSinfra$	1.4995	2.1582**	0.0205
$ICTinfra$	0.7921	3.5643*	0.0004
$WATERinfra$	0.1339	0.2529	0.8005
$AGRICinfra$	0.8120	3.5918*	0.0004
CU	0.7921	3.5644*	0.0004
FDI	0.7996	3.7828*	0.0002
FSD	0.7968	3.9595*	0.0001

* = significant at 1% **= significant at 5%
Source: Authors' computation using e-views 9.0, 2023

From the above result, all variables have correct sign. Also, the impact of all the explanatory variables on the dependent variable was statistically significant except for $WATERinfra$.

Electricity infrastructure ($ELECTinfra$) has a coefficient of 0.7952 and a t-ratio of 3.7140 and a corresponding p-value of 0.0002. This shows that an increase in electricity infrastructure by one

unit will boost employment in agricultural sector by 0.9684%. This was statistically significant at 1% level.

Transportation infrastructure ($TRANSinfra$) has a coefficient of 1.4995 and a t-ratio of 2.1582 and a corresponding p-value of 0.0205. This shows that an increase in Transportation infrastructure by one unit will boost employment in agricultural sector by 1.4995%. This was statistically significant at 5% level.

ICT infrastructure ($ICTinfra$) has a coefficient of 0.7921 and a t-ratio of 3.5643 and a corresponding p-value of 0.0000. This shows that an increase in ICT infrastructure by one unit will boost employment in agricultural sector by 0.7921%. This was statistically significant at 1% level.

Agricultural infrastructure ($AGRICinfra$) has a coefficient of 0.8120 and a t-ratio of 3.5918 and a corresponding p-value of 0.0004. This shows that an increase in agricultural infrastructure by one unit will boost employment in agricultural sector by 0.8120%. This was statistically significant at 1% level.

Capacity utilization (CU) has a coefficient of 0.7921 and a t-ratio of 3.5644 and a corresponding p-value of 0.0004. This shows that an increase in capacity utilization by one unit will boost employment in agricultural sector by 0.7921%. This was statistically significant at 1% level.

Foreign Direct Investment (FDI) has a coefficient of 0.7996 and a t-ratio of 3.7828 and a corresponding p-value of 0.0002. This shows that an increase in FDI by one unit will boost employment in agricultural sector by 0.7996%. This was statistically significant at 1% level.

Financial sector development (FSD) has a coefficient of 0.7968 and a t-ratio of 3.9595 and a corresponding p-value of 0.0001. This shows that an increase in financial sector development by

one unit will boost employment in agricultural sector by 0.7968%. This was statistically significant at 1% level.

The impact of water infrastructure on employment in agricultural sector though positive was not statistically significant even at 10% level.

4.5.4a Model 4: Manufacturing Sector Performance Model - Short Run Coefficients of Variables

The estimation result of the manufacturing sector output model which shows the short run coefficients of variables is presented in the table below:

Table 4.19a: Short Run Coefficients for Variables in the Manufacturing Sector Performance Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
$EMPLOY_MAF$	0.320849	0.409959	0.782636	0.4345
$ELECTinfra$	0.006952	0.075420	0.092179	0.9266
$TRANSinfra$	0.032093	1.403280	-0.022870	0.9818
$ICTinfra$	0.000103	1.94E-05	5.301284*	0.0000
$WATERinfra$	0.921623	0.558606	1.649863**	0.1000
$AGRICinfra$	0.380169	0.176866	2.149477*	0.0324
CU	6.88E-11	4.60E-11	1.495700	0.1358
FDI	0.010719	0.022083	0.485386	0.6278
FSD	0.092263	0.356582	0.258742	0.7960

* = significant at 1% **= significant at 5%

Source: Authors' computation using e-views 9.0, 2023

Table 4.19b: J-Statistics

J-statistic	5.607329
Prob(J-statistic)	0.617762

Source: Authors computation using e-views 9.0, 2023

From the above result, the J-statistics has a coefficient of 5.6073 and a probability value of 0.6177. Since the probability value is greater than 0.05, the null hypothesis which states that the instruments are not valid is rejected. This implies that the instruments are valid and hence the results are consistent.

Also, in the result, all the variables met sign expectation. However, most of the variables were not statistically significant even at 10% level. Only ICT infrastructure and agricultural infrastructure were statistically significant at 1% and 5% significant level for ICT infrastructure and agricultural infrastructure respectively.

The existence of serial correlation among the residuals was tested using Arellano-Bond serial correlation test. The result is presented in the table below:

Table 4.20: Arellano-Bond Serial Correlation Test

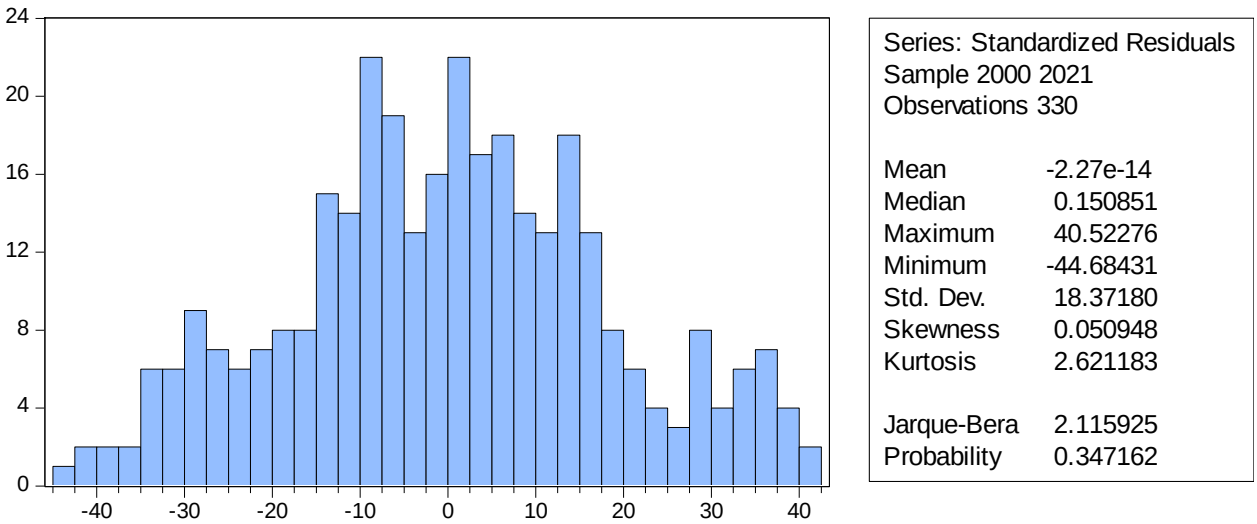
Test order	m-Statistic	rho	SE(rho)	Prob.
AR(1)	0.345518	8.100506	23.444498	0.7297
AR(2)	-0.279763	-12.030644	43.003051	0.7797

Source: Authors computation using e-views 9.0, 2023

From the above result, the probability values of AR(1) and AR(2) are 0.7297 and 0.7797 respectively. Since these values are greater than 0.05, the null hypothesis of the existence of serial correlation is rejected against the alternative hypothesis. Hence it can be concluded that there is no serial correlation among the error terms in the model.

The normality of the residual distribution was tested for using histogram. The result is presented below:

Figure 4.6



Source: Authors' computation using e-views 9.0, 2023

From the result, the skewness coefficient was 0.0509 with kurtosis of 2.6211. This shows a normal distribution with a standard normal kurtosis. The overall test for normality is shown by the Jarque-Bera statistics. The Jarque-Bera has a coefficient of 2.1159 with a probability of 0.3471. Since the probability value is greater than 0.05, it can be concluded that the residual is normally distributed.

4.5.4b Model 4: Manufacturing Sector Performance Model – Long Run Coefficients of Variables

Given the good performance of the diagnostic test, it is safe to proceed to compute the long run coefficient which is most useful for policy simulation. The coefficients of variables are shown in the table below:

Table 4.21: Long Run Coefficients for Variables in Manufacturing Sector Output Model

Variables	Coefficients	t – Statistics	P – Value
$EMPLOY_MAF$	0.5039	2.2127**	0.0244
$ELECTinfra$	0.0272	2.7124*	0.0001
$TRANSinfra$	1.2006	7.3559*	0.0000
$ICTinfra$	0.1462	2.0496**	0.0368
$WATERinfra$	-1.2061	-0.6471	0.5181
$AGRICinfra$	-1.2481	-0.1709	0.8644
CU	0.1463	2.0529**	0.0467
FDI	0.3686	2.9843*	0.0000
FSD	0.1241	1.8293***	0.0690

* = significant at 1% **= significant at 5% ***= significant at 10%

Source: Authors' computation using e-views 9.0, 2023

From the above result, all variables have correct sign except water infrastructure ($WATERinfra$) and Agriculture infrastructure ($AGRICinfra$). Also, the impact of all the explanatory variables on the dependent variable was statistically significant except for water infrastructure ($WATERinfra$) and Agriculture infrastructure ($AGRICinfra$).

Employment in the manufacturing sector ($EMPLOY_MAF$) has a coefficient of 0.5039 with a t-statistics of 2.2127 and a corresponding p-value of 0.0244. This shows that an increase in employment in the manufacturing sector by one unit will lead to an increase in manufacturing sector output by 0.5039%. This impact was statistically significant at 5% level.

Electricity infrastructure ($ELECTinfra$) has a coefficient of 0.0272 and a t-ratio of 2.7124 and a corresponding p-value of 0.0001. This shows that an increase in electricity infrastructure by one unit will lead to increase in manufacturing sector output by 0.0272%. This was statistically significant at 1% level.

Transportation infrastructure ($TRANSinfra$) has a coefficient of 1.2006 and a t-ratio of 7.3559 and a corresponding p-value of 0.0000. This shows that an increase in Transportation infrastructure by one unit will lead to increase in manufacturing sector output by 1.2006%. This was statistically significant at 1% level.

ICT infrastructure ($ICTinfra$) has a coefficient of 0.1462 and a t-ratio of 2.0496 and a corresponding p-value of 0.0368. This shows that an increase in ICT infrastructure by one unit will lead to increase in manufacturing sector output by 0.1462%. This was statistically significant at 5% level.

Capacity utilization (CU) has a coefficient of 0.1463 and a t-ratio of 2.0529 and a corresponding p-value of 0.0467. This shows that an increase in capacity utilization by one unit will lead to increase in manufacturing sector output by 0.1463%. This was statistically significant at 5% level.

Foreign Direct Investment (FDI) has a coefficient of 0.3686 and a t-ratio of 2.9843 and a corresponding p-value of 0.0000. This shows that an increase in FDI by one unit will lead to

increase in manufacturing sector output by 0.3686%. This was statistically significant at 1% level.

Financial sector development (FSD) has a coefficient of 0.1241 and a t-ratio of 1.8293 and a corresponding p-value of 0.0690. This shows that an increase in financial sector development by one unit will lead to increase in manufacturing sector output by 0.1241%. This was statistically significant at 10% level.

The impact of water infrastructure and agricultural infrastructure on manufacturing sector output were negative and also not significantly different from zero.

4.5.5a Model 5: Manufacturing Sector Employment Model - Short Run Coefficients of Variables.

The estimation result of the manufacturing sector employment model which shows the short run coefficients of variables is presented in the table below:

Table 4.22a: Short Run Coefficients for Variables in Manufacturing Sector Employment

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMPLOY_MAF(-1)	0.904369	0.114807	7.877310*	0.0000
$ELECTinfra$	-0.002905	0.023989	-0.121078	0.9037
$TRANSinfra$	0.962585	1.620337	0.594064	0.5530
$ICTinfra$	1.47E-05	1.54E-05	0.958450	0.3387
$WATERinfra$	0.107298	0.088117	1.217683	0.2244
$AGRICinfra$	0.025320	0.042272	0.598981	0.5497
CU	-1.45E-10	1.47E-10	-0.984350	0.3258
FDI	0.000718	0.004427	0.162218	0.8713
FSD	0.019022	0.038241	0.497417	0.6193

Source: Authors' computation using e-views 9.0, 2023. *significant at 1% level of significance.

Table 4.22b: J-Statistics

J-statistic	6.129481
Prob(J-statistic)	0.524715

Source: Authors computation using e-views 9.0, 2023

From the above result, the J-statistics has a coefficient of 6.129481 and a probability value of 0.524715. Since the probability value is greater than 0.05, the null hypothesis which states that the instruments are not valid is rejected. This implies that the instruments are valid and hence the results are consistent.

The results also show that all the variables met sign expectation except for $ELECTinfra$ and CU. Again, most of the variables were statistically significant except for $ELECTinfra$ and CU. The existence of serial correlation among the residuals was tested using Arellano-Bond serial correlation test. The result is presented in the table below:

Table 4.23: Arellano-Bond Serial Correlation Test

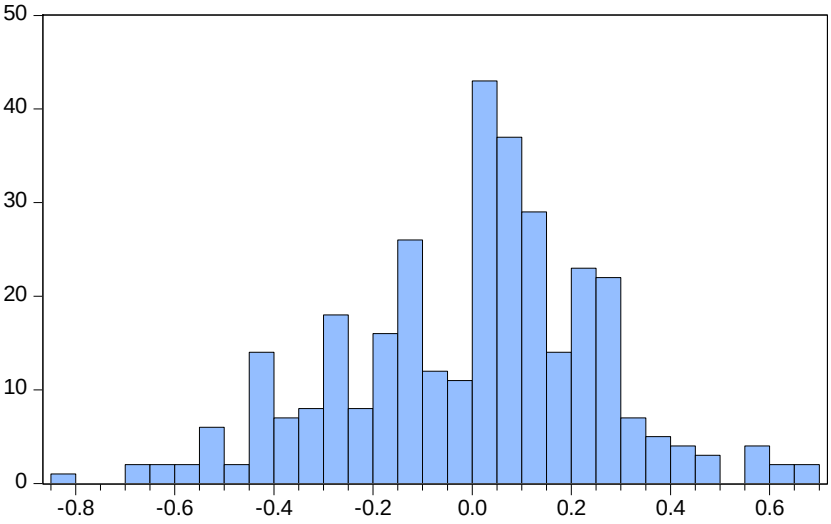
Test order	m-Statistic	rho	SE(rho)	Prob.
AR(1)	1.609040	73.041131	45.394237	0.1076
AR(2)	1.123218	41.240815	36.716670	0.2613

Source: Authors computation using e-views 9.0, 2023

From the above result, the probability values of AR(1) and AR(2) are 0.1076 and 0.2613 respectively. Since these values are greater than 0.05, the null hypothesis of the existence of serial correlation is rejected against the alternative hypothesis. Hence it can be concluded that there is no serial correlation among the error terms in the model.

The normality of the residual distribution was tested for using histogram. The result is presented below:

Figure 4.7



Source: Authors' computation using e-views 9.0, 2023

From the result, the skewness coefficient was -0.279924 with kurtosis of 3.101817. This shows a normal distribution with a standard normal kurtosis. The overall test for normality is shown by the Jarque-Bera statistics. The Jarque-Bera has a coefficient of 4.452196 with a probability of 0.107949. Since the probability value is greater than 0.05, it can be concluded that the residual is normally distributed.

4.5.5b Model 5: Manufacturing Sector Employment Model – Long run Coefficients of Variables

Given the good performance of the diagnostic test, it is safe to proceed to compute the long run coefficient which is most useful for policy simulation. The coefficients of variables are shown in the table below:

Table 4.24: Long run Coefficients for Variables in Manufacturing Sector Employment Model

Variables	Coefficients	t – Statistics	P – Value
$ELECTinfra$	0.9046	7.9175*	0.0000
$TRANSinfra$	0.2320	10.4760*	0.0000
$ICTinfra$	0.9043	7.8772*	0.0000
$WATERinfra$	0.9057	7.0648*	0.0000
$AGRICinfra$	0.9025	7.7196*	0.0000
CU	0.9043	7.8773*	0.0000
FDI	0.9043	7.8563*	0.0000
FSD	2.9028	7.65778	0.0000

* = significant at 1% **= significant at 5% ***= significant at 10%

Source: Authors' computation using e-views 9.0, 2023

From the above result, all variable have correct sign. Also, the impact of all the explanatory variables on the dependent variable was statistically significant at 1% level.

Electricity infrastructure ($ELECTinfra$) has a coefficient of 0.9046 and a t-ratio of 7.9175 and a corresponding p-value of 0.0000. This shows that an increase in electricity infrastructure by one unit will boost employment in manufacturing sector by 0.9046%. This was statistically significant at 1% level.

Transportation infrastructure ($TRANSinfra$) has a coefficient of 0.2320 and a t-ratio of 10.4760 and a corresponding p-value of 0.0000. This shows that an increase in Transportation infrastructure by one unit will boost employment in manufacturing sector by 0.2320%. This was statistically significant at 1% level.

ICT infrastructure ($ICTinfra$) has a coefficient of 0.9043 and a t-ratio of 7.8772 and a corresponding p-value of 0.0000. This shows that an increase in ICT infrastructure by one unit will boost employment in manufacturing sector by 0.9043%. This was statistically significant at 1% level.

Water infrastructure ($WATERinfra$) has a coefficient of 0.9057 and a t-ratio of 7.0648 and a corresponding p-value of 0.0000. This shows that an increase in water infrastructure by one unit will boost employment in manufacturing sector by 0.9057%. This was statistically significant at 1% level.

Agricultural infrastructure ($AGRICinfra$) has a coefficient of 0.9025 and a t-ratio of 7.7196 and a corresponding p-value of 0.0000. This shows that an increase in agricultural infrastructure by one unit will boost employment in manufacturing sector by 0.9025%. This was statistically significant at 1% level.

Capacity utilization (CU) has a coefficient of 0.9043 and a t-ratio of 7.8773 and a corresponding p-value of 0.0000. This shows that an increase in capacity utilization by one unit will boost employment in manufacturing sector by 0.9043%. This was statistically significant at 1% level.

Foreign Direct Investment (FDI) has a coefficient of 0.9043and a t-ratio of 7.8563 and a corresponding p-value of 0.0000. This shows that an increase in FDI by one unit will boost employment in manufacturing sector by 0.9043%. This was statistically significant at 1% level.

Financial sector development (FSD) has a coefficient of 0.9028 and a t-ratio of 7.6577 and a corresponding p-value of 0.0001. This shows that an increase in financial sector development by one unit will boost employment in manufacturing sector by 0.7968%. This was statistically significant at 1% level.

4.6 Evaluation of Research hypotheses.

To evaluate the hypotheses which guided this study, the researcher recalls the null hypotheses earlier stated.

H_{01}: Infrastructural development has no significant impact on aggregated real sector in the ECOWAS region;

H_{02}: Infrastructural development has no significant impact on disaggregated agricultural sector performance in the ECOWAS region;

H_{03}: Infrastructural development has no significant influence on employment in agriculture sector in the ECOWAS region;

H_{04}: Infrastructural development has no significant effect on disaggregated manufacturing sector performance ECOWAS region;

H_{05}: Infrastructural development has no significant impact on employment in manufacturing sector in the ECOWAS region;

Hypothesis One - Infrastructural development has no significant impact on aggregated real sector performance in the ECOWAS region

The results of the GMM estimation in model 1 – real sector performance $AGRMAF_GDP$ (using the long run coefficients) - show that the variables used to measure infrastructural development had positive signs, t – values greater 2 and p – values less than 0.05. All these imply that infrastructural development significantly impacts on real sector performance $AGRMAF_GDP$ in the ECOWAS region. Therefore, we reject the null hypotheses that there is no significant impact of infrastructural development on aggregated real sector performance in the ECOWAS region and accept that infrastructural development has a significant impact of aggregated real sector performance in the ECOWAS region.

Hypothesis Two - Infrastructural development has no significant impact on disaggregated agricultural sector performance in the ECOWAS region

The results of the GMM estimation in model 2 – disaggregated agricultural sector performance AGR_GDP (using the long run coefficients) - show that the variables used to measure

infrastructural development had positive signs, t – values greater 2 and p – values less than 0.05. All these imply that infrastructural development significantly impacts on disaggregated agricultural sector performance AGR_GDP in the ECOWAS region. Therefore, we reject the null hypotheses that there is no significant impact of infrastructural development on disaggregated agricultural sector performance in the ECOWAS region and accept that infrastructural development has a significant impact of disaggregated agricultural sector performance in the ECOWAS region.

Hypothesis Three - Infrastructural development has no significant influence on employment in agricultural sector in the ECOWAS region

The results of the GMM estimation in model 3 - agricultural sector employment $EMPLOY_AGR$ (using the long run coefficients)-show that the variables used to measure infrastructural development had positive signs, t – values greater 2 and p – values less than 0.05. All these imply that infrastructural development significantly impacts on agricultural sector employment $EMPLOY_AGR$ in the ECOWAS region. Therefore, we reject the null hypotheses that there is no significant impact of infrastructural development on agricultural sector employment in the ECOWAS region and accept that infrastructural development has a significant impact of agricultural sector employment in the ECOWAS region.

Hypothesis Four - Infrastructural development has no significant influence on disaggregated manufacturing sector performance in the ECOWAS region.

The results of the GMM estimation in model 4 – disaggregated manufacturing sector performance MAF_GDP (using the long run coefficients) - show that the variables used to measure infrastructural development had positive signs, t – values greater 2 and p – values less

than 0.05. All these imply that infrastructural development significantly impacts on disaggregated manufacturing sector performance MAF_GDP in the ECOWAS region. Therefore, we reject the null hypotheses that there is no significant impact of infrastructural development on disaggregated manufacturing sector performance in the ECOWAS region and accept that infrastructural development has a significant impact of disaggregated manufacturing sector performance in the ECOWAS region.

Hypothesis Five - Infrastructural development has no significant influence on employment in the manufacturing sector in the ECOWAS region

The results of the GMM estimation in model 5 - manufacturing sector employment $EMPLOY_MAF$ (using the long run coefficients) - show that the variables used to measure infrastructural development had positive signs, t – values greater 2 and p – values less than 0.05. All these imply that infrastructural development significantly impacts on manufacturing sector employment $EMPLOY_MAF$ in the ECOWAS region. Therefore, we reject the null hypotheses that there is no significant impact of infrastructural development on manufacturing sector employment in the ECOWAS region and accept that infrastructural development has a significant impact of manufacturing sector employment in the ECOWAS region.

4.7 Discussion of Findings.

This part of the research focuses on the discussion of findings based on the estimation of the specified models and regression results as presented in the previous section. Five models were designed to capture the main objectives and specific objectives respectively.

From the results of the descriptive statistics presented in table 4.6, the condition of the real sector in the ECOWAS region denoted by $AGRMAF_GDP$ indicates robustness given the maximum

value of 80.91 and minimum value of 11.27. It shows improvement overtime as well as the difference in the level attained by the different economies (as far as real sector is concerned) as the standard deviation is as high as 11.8729. The real sector considered as an amalgam of the agricultural and manufacturing sectors in the study remains a driver of growth in the region as the results have shown.

The performance of the agricultural sector is denoted by AGR_GDP. The maximum value of 79.04% minimum value of 4.63% and standard deviation of 13.47% are indicative of the fact that agriculture is predominant in the region. The level of agricultural development seems not to vary across the 15 member countries that make up the ECOWAS sub-region as the result of the standard deviation suggests.

For the manufacturing sector performance, denoted by MAF_GDP, the results show a maximum value of 21.49% and a minimum value of 1.53% and standard deviation as low as 4.36%. This is a clear indication of the near absence of manufacturing activities in the sub-region. This may be responsible for the high importation of finished manufactured goods into the sub region. The few manufacturing outfits within the sub-region are operating below installed capacity and as such cannot be optimal.

The results show that more persons were employed in the agricultural sector than the manufacturing sector in the period under review given the minimum values and maximum value for both sectors respectively. On the average employment was 49.29% in the agricultural sector and 15% of the labour force was employed in the manufacturing sector.

Access to electricity was among the indicators used to measure infrastructural development in the sub-region for this study. The results show that on the average about 36.67% has access to

electricity in the ECOWAS region. Electricity distribution in the ECOWAS region has been abysmally poor. The standard deviation of 22.41 among other things indicates that the state of electricity in the region is similar across countries that make up the region.

The results for ICT infrastructure show the highest level of discrepancy (maximum value -204.2548 and minimum value -0.000). It implies a brilliant performance. ICT infrastructure seems to be penetrating the sub-region at a faster pace. Quite a number of persons in the region have access to ICT facilities in the sub region.

For water infrastructure denoted by $AGRICinfra$, the descriptive statistics results show that on the average, 45.48% of the population had access agricultural infrastructure. Access to agricultural infrastructure remains a challenge to most communities in the ECOWAS region. The standard deviation of 17.300 indicates that the situation is not different among the countries of the region.

However the negative value of skewness for the agricultural employment shows that less people are being employed by the sector over the years. Agricultural land also has a negative skew and these negative skewness indicate that the ECOWAS region is increasingly losing agricultural inputs (land) to other sectors as well as factors).

The results of the panel unit root test indicate that all the variables have unit root except MAF_GDP, $WATERinfra$ $AGRICinfra$ and FDI. This implies that these variables were stationary at levels and hence integrated of order zero I(0). $AGRMAF_GDP$, AGR_GDP, $EMPLOY_AGR$, $EMPLOY_MAF$, $ELECTinfra$, $TRANSinfra$, $ICTinfra$ and CU were subjected to unit root test at first order difference. They became stationary afterwards and hence integrated of order one I(1)

The results of the Pedroni Residual co-integration results as presented in tables 4.9a and 4.9b indicate that the variables are co-integrated given that their probability values are below 0.05. Therefore, a long run relationship can be said to exist among the variables of the model. This test has become necessary since the variables are integrated of different orders.

As noted earlier, five models were used to capture the objectives of this study. These models were estimated using the GMM methodology. We shall discuss the results model by model (short run coefficient and long run coefficient).

For **Model 1 aggregated real sector performance**, in the short run, the results indicate a positive relation existing between the variables of model and $AGRMAF_GDP$ since sign expectations were met except CU which was negative. The results also indicates that all the variables used to capture infrastructural development and the control variables of the model CU,FDI and FSD were not statistically significant at 5% level of significance in the short run. This, however, means that the effect of infrastructural development on real sector performance in the short run is not significant. This may be due to delayed effects. The impact of infrastructural development on real sector performance in the ECOWAS region is minimal in the short run as the results of this study suggests. The results of the J - statistics indicates that instruments are valid since the probability value of 0.2848 is greater than 0.05. This clearly implies that the results are consistent and that the model is suitable for the analysis. The results of the serial correlation test suggest that there is no correlation among the error terms in the model. The normality of the residual which was tested for using the histogram indicates that the residual is normally distributed.

In the long run, the variables all met the sign expectations. The impact of the explanatory variables on $AGRMAF_GDP$ was statistically significant except for CU and $WATERinfra$.

Employment in the agricultural sector denoted by $EMPLOY_AGR$ was shown to be significant determinant of $AGRMAF_GDP$ as the result of this study indicate a t -value of 2.4322 which is clearly greater than 2 and a probability of value of 0.0008 which is less than 0.05 suggest that a statistically significant positive relationship exists between $EMPLOY_AGR$ and $AGRMAF_GDP$. This result is expected since employment in the agricultural sector promotes real sector performance. For this study, the real sector was taken to mean a combination of the agriculture and manufacturing sector plus employment in these sectors.

Employment in manufacturing sector denoted by $EMPLOY_MAF$ was shown to be determinant of real sector performance $AGRMAF_GDP$ as the results indicate. The t-value of 1.9017 and a p-value of 0.0133 shows that a positive relationship exists between $EMPLOY_MAF$ and $AGRMAF_GDP$. This is expected since employment in the manufacturing sector shows an expansion of the manufacturing sector. Again, this study takes the real sector performance to mean a combination of the agriculture and manufacturing sectors including employment in these sectors.

Electricity infrastructure demoted by $ELECTinfra$ was shown to be a significant determinant of real sector performance denoted by $AGRMAF_GDP$ as the results of this study reveal. The t-ratio of 2.5340 and a p-value of 0.0000 implies that a positive relationship exists between the two variables. An increase in electricity access leads to a significant improvement in real sector performance. Electricity plays a crucial role in promoting manufacturing/production activities. Electricity is needed to power machines that are used in storage and processing of agricultural products. This finding is in line with those of Ekeocha *et al* (2002) and Horvat *et al* (2020) and contrast with those of Edeme *et al* (2022a).

For transport infrastructure denoted by $TRANSinfra$, the results of this study indicate that an increase in transportation infrastructure will lead to an increase in real sector performance denoted by $AGRMAF_GDP$. The t-value of 2.8933 and a corresponding probability value of 0.0000 imply that $TRANSinfra$ is a significant determinant of $AGRMAF_GDP$. These findings are in consonance with those of Wang *et al* (2020), Sandi *et al* (2018) and Gherghira *et al* (2018). An effective transportation system is imperative for the movement of agricultural and finished manufactured products.

The results of this study show that ICT infrastructure denoted by $ICTinfra$ is a significant determinant of real sector performance denoted by $AGRMAF_GDP$. At 1% level of significance, the results show a t-value of 0.0000. This simply implies that ICT infrastructures denoted by $ICTinfra$ is a significant determinant of real sector performance denoted by $AGRMAF_GDP$. This finding agrees with those of David (2019), David and Grobler (2020), Maji and Waziri (2020), and Cheng *et al* (2020); ICT impacts positively on productivity. It provides very feasible options for production, processing, marketing and distribution for households, farmers and firms.

In the same vein, the results of this study show that foreign direct investment FDI and Financial sector development FSD are both significant determinants of real sector performance denoted by $AGRMAF_GDP$. Given their t-value of 3.8033 and 2.7955 and a corresponding p-value of 0.0000 and 0.0000 respectively, both FDI and FSD are statistically significant at the 1% level. This finding is in line with the findings of Ogundipe *et al* (2020). FDI brings with it, capital, technological know-how and improves the ways of doing things, thus bringing about enhanced economic performance. The inflow of FDI into developing countries has created jobs, increased productive capacity and boosted agricultural production through mechanized farming.

From the results, water infrastructure denoted by $WATERinfra$ and capacity utilization CU was shown not to be significant determinants of $AGRMAF_GDP$. Though a positive relationship exists between $WATERinfra$ and CU, the effect they exert on real sector performance is minimal. This is strange. Water resources abound in the ECOWAS region. In the desert area of the region irrigational facilities are provided for in order to nourish plants and also for farm use. However the effects of the change in climatic conditions may account for this. Inadequate technical know-how in the ECOWAS region results in low capacity utilization. Lack of adequately trained manpower may lead to underutilization of installed capacity.

Model 2 captures disaggregated agricultural sector performance AGR_GDP (short run). The results indicate that all the variables used to capture infrastructural development – $EMPLOY_AGR, ELECTinfra, TRANSinfra, ICTinfra, WATERinfra, AGRICinfra$ exhibit a positive relationship with agricultural sector performance denoted by AGR_GDP. They all met sign expectations except FDI which was negative. The variables of the model were not statistically significant at 5% in the short run. This means that in the short run, the effect of infrastructural development on AGR_GDP is minimal. This may however be as a result of delayed effect. The result of the J-statistic indicate that instruments are valid since the probability value 0.3942 is greater than 0.05. This clearly implies that the results are consistent and that the model is suitable for the analysis. The results of the serial correlation test suggest that there is no correlation among the error terms in the model. The normality of the residual which was tested for using the histogram indicates that the residual is normally distributed.

In the long run, all the variables met sign expectations except financial sector development FSD that has negative. The impact of the explanatory variables on AGR_GDP was statistically significant. Employment in the agricultural sector denoted by $EMPLOY_AGR$ was shown to be a

significant determinant of agricultural sector performance denoted by AGR_GDP. The result shows a t-value of 1.9927 and a correspondence p-value of 0.0439 thus implying that a positive and statistically significant relationship exists between $EMPLOY_AGR$ and AGR_MAF. This is expected since increasing employment in the agricultural sector simply implies an expansion in the sector. This finding is similar to those of Edeme *et al* (2020a)

Electricity infrastructure denoted by $ELECTinfra$ also was shown to be a significant determinant of agricultural sector performance. The results show a t-value of 3.8662 and a corresponding p-value of 0.0001 implying statistical significance at 1% level. An increase in access to electricity impacts positively on agricultural sector performance. Electricity is used to power processing and storage facilities for agricultural products. Again, this finding agrees with those of Ekeocha *et al* (2022), and Horvat *et al* (2020). Electricity is vital for the growth and development of the agricultural sector.

Transport infrastructure denoted by $TRANSinfra$ also was shown to be a significant determinant of agricultural sector performance. The results show a t-value of 12.7679 and a corresponding p-value of 0.0000 implying statistical significance at 1% level. An increase in access to transport impacts positively on agricultural sector performance. Again, this finding agrees with those of Wang *et al* (2020), Sandi *et al* (2018) and Gherghira *et al* (2018). An effective transportation system is essential for the movement of agricultural and finished manufactured products.

ICT infrastructure denoted by $ICTinfra$ was also shown to be a significant determinant of agricultural sector performance. The results show a t-value of 4.8027 and a corresponding p-value of 0.0000 implying statistical significance at 1% level. An increase in access to information and communication technology services impact positively on agricultural sector

performance. This is in agreement with David and Grobler (2020), Maji and Waziri (2020), and Cheng *et al* (2020). ICT impacts positively on productivity. It provides very feasible options for production, processing, marketing and distribution for households, farmers and firms.

Similarly, water infrastructure denoted by $WATERinfra$ was also shown to be a significant determinant of agricultural sector performance. The results show a t-value of 9.9504 and a corresponding p-value of 0.0000 implying statistical significance at 1% level. An increase in access to water infrastructure impact positively on agricultural sector performance. This means that an increase in water infrastructure by one unit will lead to increase in agricultural sector output by 14.4538%.

Agricultural infrastructure denoted by $AGRICinfra$ was also shown to be a significant determinant of agricultural sector performance. The results show a t-value of 1.8914 and a corresponding p-value of 0.0674 implying statistical significance at 10% level. For this study, agricultural infrastructure is taken to be land available for farming as a percentage of land area. An increase in access to land available for agricultural impacts positively on agricultural sector performance. Again, this finding is in line with those of Edeme *et al* (2020a).

In the same vein, Capacity Utilization CU and Foreign Direct Investment FDI from the results of this study show that they are both significant determinants of agricultural sector performance denoted by AGR_GDP. Increasing CU and FDI flows in the agricultural sector improves the performance of the sector. Edeh, Eze and Ugwuanyi (2020) agree that FDI exerts a positive and significant impact on agricultural sector output.

The results show that the impact of financial sector development on agricultural sector output is negative and also not significantly different from zero. This is quite strange as some studies like

Akpaeti (2015) have shown that financial sector development has significant impact on agricultural sector output.

Model 3 captures agricultural sector employment $EMPLOY_AGR$ (short run). The result indicates that all the variables used to capture infrastructural development except $ICTinfra$ – exhibit a negative relationship with agricultural sector employment denoted by $EMPLOY_AGR$. The variables of the model were not statistically significant at 5% in the short run. This means that in the short run, the effect of infrastructural development on $EMPLOY_AGR$ is minimal. The result of the J-statistics indicates that instruments are valid since the probability value 0.0611 is greater than 0.05. This clearly implies that the results are consistent and that the model is suitable for the analysis. The results of the serial correlation test suggest that there is no correlation among the error terms in the model. The normality of the residual which was tested for using the histogram indicates that the residual is normally distributed.

In the long run, all the variables met sign expectations and were all statistically significant at the 1% level, except $WATERinfra$ that was not significant even at 10% level. Electricity infrastructure denoted by $ELECTinfra$ also was shown to be a significant determinant of agricultural sector employment denoted by $EMPLOY_AGR$. The results show a t-value of 3.7140 and a corresponding p-value of 0.0002 implying statistical significance at 1% level. An increase in access to electricity will enhance on agricultural sector employment significantly. The results indicate that higher access to electricity improves the percentage of people employed by the agricultural sector. Specifically, an increase in the percentage of the population with access to electricity increases the percentage of people employed in the agricultural sector by about 3.7%. This is in line with the findings of Edeme *et al* (2020a).

Transport infrastructure denoted by $TRANSinfra$ also was shown to be a significant determinant of agricultural sector employment denoted by $EMPLOY_AGR$. The results show a t-value of 2.1582 and a corresponding p-value of 0.0205 implying statistical significance at 1% level. An increase in access to transportation will enhance on agricultural sector employment significantly. The results indicate that higher access to transportation improves the percentage of people employed by the agricultural sector. Specifically, an increase in the percentage of the population with access to transportation increases the percentage of people employed in the agricultural sector by about 2.1%. Again, this finding agrees with those of Wang *et al* (2020), Sandi *et al* (2018) and Gherghira *et al* (2018). An effective transportation system is essential for the movement of agricultural. This finding negates the findings of Edeme *et al* (2020a).

ICT infrastructure denoted by $ICTinfra$ also was shown to be a significant determinant of agricultural sector employment denoted by $EMPLOY_AGR$. The results show a t-value of 3.5643 and a corresponding p-value of 0.0000 implying statistical significance at 1% level. An increase in access to ICT services will enhance on agricultural sector employment significantly. The results indicate that higher access to ICT services improves the percentage of people employed by the agricultural sector. Specifically, an increase in the percentage of the population with access to ICT services increases the percentage of people employed in the agricultural sector by about 3.5%.This is in agreement with David and Grobler (2020), Maji and Waziri (2020), and Cheng *et al* (2020), but in sharp contrast with those Edeme *et al* (2020a). ICT impacts positively on productivity. It provides very feasible options for production, processing, marketing and distribution for households, farmers and firms.

The results of this study show that water infrastructure denoted by $WATERinfra$ is not a significant determinant of agricultural sector performance. The results show a t-value of 0.2529

and a corresponding p-value of 0.8005 and this clearly shows that it is not statistically significant even at 10% level. This is strange and may be attributed to the changes in the climatic conditions that have affected the ECOWAS region and the world at large.

Agricultural infrastructure denoted by $AGRICinfra$ also was shown to be a significant determinant of agricultural sector employment denoted by $EMPLOY_AGR$. The results show a t-value of 3.5918 and a corresponding p-value of 0.0004 implying statistical significance at 1% level. For this study, agricultural infrastructure is taken to be land available for farming as a percentage of land area. An increase in access to land will enhance on agricultural sector employment significantly. Specifically, an increase in access to land available for agricultural increases the number of people employed in the agricultural sector by 3.5%. Again this finding does not agree with those of Edeme *et al* (2020a).

In the same vein, Capacity Utilization CU and Foreign Direct Investment FDI from the results of this study show that they are both significant determinants of agricultural sector employment denoted by $EMPLOY_AGR$. Increasing capacity utilization and FDI flows in the agricultural sector increases the number of persons employed in the agricultural sector by 3.56% and 3.78% respectively.

Financial Sector Development denoted by FSD also was shown to be a significant determinant of agricultural sector employment denoted by $EMPLOY_AGR$. The results show a t-value of 3.9595 and a corresponding p-value of 0.0001 implying statistical significance at 1% level. An increase in access to finance will increase the number of persons employed in the agricultural sector significantly. The results indicate that financial sector development improves the percentage of people employed by the agricultural sector. Specifically, an increase in the percentage of the

population with access to financing increases the percentage of people employed in the agricultural sector by about 3.95%. Access to and availability of funds increases the demand for agricultural products. Increasing supply of agricultural products are a consequence of increased employments in the agricultural sector.

Model 4 captures disaggregated manufacturing sector performance MAF_GDP (short run). The result indicates that all the variables used to capture infrastructural development except $TRANSinfra$ – exhibit a positive relationship with manufacturing sector performance denoted by MAF_GDP. Only $ICTinfra$ and $AGRICinfra$ were statistically significant at 5% in the short run. This means that in the short run, the effect of infrastructural development on MAF_GDP is minimal. This maybe as a result of delayed effects. The result of the J-statistics indicates that instruments are valid since the probability value 0.0617 is greater than 0.05. This clearly implies that the results are consistent and that the model is suitable for the analysis. The results of the serial correlation test suggest that there is no correlation among the error terms in the model. The normality of the residual which was tested for using the histogram indicates that the residual is normally distributed.

In the long run, all the variables met sign expectations except $WATERinfra$ and $AGRICinfra$ that were negative. The impact of the explanatory variables on MAF_GDP was statistically significant excluding $WATERinfra$ and $AGRICinfra$. Employment in the manufacturing sector denoted by $EMPLOY_MAF$ was shown to be a significant determinant of manufacturing sector performance denoted by MAF_GDP. The result shows a t-value of 2.2127 and a correspondence p-value of 0.0244 thus implying that a positive and statistically significant relationship exists between $EMPLOY_AGR$ and MAF_GDP. This is expected since increasing employment in the manufacturing sector simply implies an expansion in the sector.

Electricity infrastructure denoted by $ELECTinfra$ also was shown to be a significant determinant of agricultural sector performance. The results show a t-value of 2.7124 and a corresponding p-value of 0.0001 implying statistical significance at 1% level. An increase in access to electricity impacts positively on manufacturing sector performance. Electricity is used to power machines used in production. Again, this finding agrees with those of Ekeocha *et al* (2022) and Horvat *et al* (2020) but contrasts those of Edeme *et al* (2020b). Electricity is vital for the growth and development of the manufacturing sector.

Transport infrastructure denoted by $TRANSinfra$ also was shown to be a significant determinant of manufacturing sector performance. The results show a t-value of 7.3559 and a corresponding p-value of 0.0000 implying statistical significance at 1% level. An increase in access to transport impact positively on manufacturing sector performance. Again this finding agrees with those of Wang *et al* (2020); Sandi *et al* (2018) and Gherghira *et al* (2018). An effective transportation system is essential for the movement of finished manufactured products.

ICT infrastructure denoted by $ICTinfra$ was also shown to be a significant determinant of manufacturing sector performance. The results show a t-value of 2.0496 and a corresponding p-value of 0.0368 implying statistical significance at 1% level. An increase in access to information and communication technology services impact positively on the manufacturing sector performance. This is in agreement with David and Grobler (2020), Maji and Waziri (2020), and Cheng *et al* (2020). ICT impacts positively on productivity. It provides very feasible options for production, processing, marketing and distribution for households, farmers and firms.

In the same vein, Capacity Utilization CU, Foreign Direct Investment FDI and Financial Sector Development FSD, from the results of this study show that they are significant determinants of manufacturing sector performance denoted by MAF_GDP. Increasing capacity utilization,

financial inclusion and FDI flows in the manufacturing sector improves the performance of the sector. Edeme *et al* (2020b) confirms the positive effect of capacity utilization, capital expenditure by government on manufacturing sector performance in Nigeria.

Water infrastructure denoted by $WATERinfra$ and agricultural infrastructure denoted by $AGRICinfra$ were shown to be no significant determinants of manufacturing sector performance. The result of this study indicates that there seem to be no relationship between $WATERinfra$, $AGRICinfra$ and manufacturing sector performance denoted by MAF_GDP.

Model 5 captures manufacturing sector employment $EMPLOY_AGR$ (short run). The result indicates that all the variables used to capture infrastructural development except $ELECTinfra$ and CU exhibit a positive relationship with manufacturing sector employment denoted by $EMPLOY_MAF$. The variables of the model were not statistically significant at 5% in the short run. This means that in the short run, the effect of infrastructural development on $EMPLOY_MAF$ is minimal. This maybe as a result of delayed effects. The result of the J-statistics indicates that instruments are valid since the probability value 0.5247 is greater than 0.05. This clearly implies that the results are consistent and that the model is suitable for the analysis. The results of the serial correlation test suggest that there is no correlation among the error terms in the model. The normality of the residual which was tested for using the histogram indicates that the residual is normally distributed.

In the long run, all the variables met sign expectations and were all statistically significant at the 1% level. Electricity infrastructure denoted by $ELECTinfra$ was shown to be a significant determinant of manufacturing sector employment denoted by $EMPLOY_MAF$. The results show a t-value of 7.9175 and a corresponding p-value of 0.0000 implying statistical significance at 1%

level. An increase in access to electricity will enhance on manufacturing sector employment significantly. The results indicate that higher access to electricity, improves the percentage of people employed by the manufacturing sector. Specifically, an increase in the percentage of the population with access to electricity increases the percentage of people employed in the manufacturing sector by about 0.9%. This is in line with the findings of Ekeocha *et al* (2021) and Umofia *et al* (2018).

Transport infrastructure denoted by $TRANSinfra$ was also shown to be a significant determinant of manufacturing sector employment denoted by $EMPLOY_MAF$. The results show a t-value of 10.4760 and a corresponding p-value of 0.0000 implying statistical significance at 1% level. An increase in access to transportation will enhance manufacturing sector employment significantly. The results indicate that higher access to transportation improves the percentage of people employed by the manufacturing sector. Specifically, a unit increase in the percentage of the population with access to transportation increases the percentage of people employed in the manufacturing sector. Again, this finding agrees with those of Wang *et al* (2020), Sandi *et al* (2018) and Gherghira *et al* (2018). An effective transportation system is essential for the movement of manufactured finished products.

ICT infrastructure denoted by $ICTinfra$ was shown to be a major determinant of manufacturing sector employment denoted by $EMPLOY_MAF$. The results show a t-value of 7.8772 and a corresponding p-value of 0.0000 implying statistical significance at 1% level. An increase in access to ICT services will enhance on manufacturing sector employment significantly. The results indicate that higher access to ICT services improves the percentage of people employed by the manufacturing sector. Specifically, an increase in the percentage of the population with access to ICT services increases the percentage of people employed in the agricultural sector by

about 0.9%. This is in agreement with the findings of David and Grobler (2020), Maji and Waziri (2020) and Cheng *et al* (2020); but in sharp contrast with those Edeme *et al* (2020a). ICT impacts positively on productivity. It provides very feasible options for production, processing, marketing and distribution for households, farmers and firms.

The results of this study show that water infrastructure denoted by $WATERinfra$ is a significant determinant of manufacturing sector performance. The results show a t-value of 7.0648 and a corresponding p-value of 0.0000 and this clearly shows that it is statistically significant at 1% level.

Agricultural infrastructure denoted by $AGRICinfra$ also was shown to be a significant determinant of manufacturing sector employment denoted by $EMPLOY_MAF$. The results show a t-value of 7.7196 and a corresponding p-value of 0.0000 implying statistical significance at 1% level. For this study, agricultural infrastructure is taken to be land available for farming as a percentage of land area. An increase in access to land will enhance manufacturing sector employment significantly. Specifically, a unit increase in access to land available for agriculture increases the number of people employed in the manufacturing sector. Greater access to land increases agricultural output which in turn may translate to more raw materials for manufacturing sector usage. Again, this finding does not agree with those of Edeme *et al* (2020a).

In the same vein, Capacity Utilization CU, Foreign Direct Investment FDI and Financial Sector Development FSD were shown to be significant determinants of manufacturing sector employment denoted by $EMPLOY_MAF$. Increasing capacity utilization, FDI flows and

financial inclusion in the manufacturing sector increases the number of persons employed in the sector significantly.

4.8 Policy Implications

The findings of this research work have brought to the fore a number of issues that shall advance policy simulations and promote further research in the ECOWAS region and beyond. Some of the policy implications derived from these empirical results are listed below:

1. Infrastructural development is a veritable tool for influencing real sector performance in the ECOWAS region. The rapid incremental economic growth and development witnessed in the sub-region within the last decade are direct consequence of the infrastructural development measures in the region. As noted earlier, the real sector, for the purpose of this study, is taken to mean a combination of agriculture sector and the manufacturing sector. It is considered as an engine of growth in an economy.
2. The infrastructural development exerts a significant effect on agricultural sector performance in the ECOWAS region. Agriculture is a major employer of labour in the sub-region and also source of food for human consumption as well as source of raw materials for industrial use. The ECOWAS region is blessed with a vast expanse of land that is rich, cultivatable and friendly climatic conditions.
3. Manufacturing sector performance in the ECOWAS region depends on the level of infrastructural development. Electricity and ICT infrastructures measured by access to electricity and ICT composite index respectively are vital for the optimum performance of the manufacturing sector in the ECOWAS region.
4. Infrastructural development is imperative for creation of employment in both the agricultural and manufacturing sectors in the ECOWAS region.

5. Foreign Direct Investment FDI and Financial Sector Development FSD have shown to be determinants of real sector performance as expected.

CHAPTER FIVE

SUMMARY OF FINDINGS, CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter is wholly dedicated to the concluding part of this research work. It consists of summary of findings, recommendations, conclusion, contribution to knowledge and agenda for further empirical research.

5.2 Summary of Findings

This study was motivated by the paucity of studies in the extant literature on the infrastructure–real sector nexus in the ECOWAS region, especially studies that centred on the roles of infrastructure in enhancing real sector performance at aggregated and disaggregated level. This study, therefore, sought to ascertain the impact of infrastructural development on aggregated real sector performance in the ECOWAS region, taking the real sector to mean an amalgam of the agricultural and manufacturing sector performance. This was done with the aid of the following specific objectives:

i. determine the effect of infrastructural development on aggregated real sector performance in the ECOWAS region;
ii. examine the impact of infrastructural development on disaggregated agricultural sector performance in the ECOWAS region;
ii. ascertain the influence of infrastructural development on employment in agriculture sector in the ECOWAS region;
iii. determine the effect of infrastructural development on disaggregated manufacturing sector performance in the ECOWAS region;
iv. evaluate the impact of infrastructural development on employment in manufacturing sector in the ECOWAS region.

The study adopted the GMM methodology in investigating the effects of infrastructural development on real sector performance in the ECOWAS region. Data for the study were sourced from World Development Indicators (WDI) and Africa Infrastructure Development Index (AIDI) as published by the World Bank and African Development Bank respectively. The summary of the findings of this study includes:

1. The results show that infrastructural development captured with $ELECTinfra$, $TRANSinfra$, ICTinfra, $WATERinfra$ and $AGRICinfra$ in the short run were shown to be positive but did not have significant impact on real sector performance denoted by $AGRMAF_GDP$. In the long run all the variables used to capture infrastructural development had positive and significant impact on $AGRMAF_GDP$.
2. In the short run infrastructural development stimulates agricultural sector performance denoted by AGR_GDP. This impact though positive, is not significant. In the long run all the variables used to capture infrastructural development $ELECTinfra$, $TRANSinfra$, ICTinfra, $WATERinfra$ and $AGRICinfra$ were shown to stimulate agricultural sector performance denoted by AGR_GDP. The long run results are in consonance with the findings of Ekeocha *et al* (2020), Horvat *et al* (2020), Wang *et al* (2020), Sandi *et al* (2018), Gherghira *et al* (2018), Cheng *et al* (2020), Edeme *et al* (2020a), Edeh, Eze and Ugwuanyi (2020) and in contrast with those of Akpaeti (2015).
3. The result indicates that in the short run infrastructural development does not stimulate agricultural sector employment denoted by $EMPLOY_AGR$. In the long run the result reveal that infrastructural development captured by $ELECTinfra$, $TRANSinfra$, ICTinfra, $WATERinfra$ and $AGRICinfra$ has a significant impact on agricultural sector employment denoted by $EMPLOY_AGR$. The long run result tend to agree with those of

Wang et al (2020), Sandi et al (2018), Gherghira et al (2018), and Cheng et al (2020) but negates those of Edeme *et al* (2020a).

4. The findings of the study show that in the short run all the variables used to capture infrastructural development except $TRANSinfra$ stimulate manufacturing sector performance denoted by MAF_GDP. In the long run, except $WATERinfra$ and $AGRICinfra$, all the variables used to capture infrastructural development were shown to stimulate manufacturing sector performance. The long run results are in line with those of Ekeocha *et al* (2020), Wang *et al* (2020), Sandi *et al* (2018), Gherghira *et al* (2018), Cheng *et al* (2020) and Edeme *et al* (2020b).
5. The results of this study except $ELECTinfra$ show that all the other variables used to capture infrastructural development had a positive but non-significant relationship with manufacturing sector employment denoted by $EMPLOY_MAF$ in the short run. In the long run infrastructure development stimulates manufacturing sector performance ($EMPLOY_MAF$).

   The control variables of the model ($CU, FDI, FSD,$) were shown to stimulate the growth and performance of the real sector in long run as confirmed by Ogundipe *et al* (2020)

5.3 Conclusion

The result of this study has thrown up a number of issues. Central among them is the pivotal role that infrastructural development plays in stimulating real sector performance in the ECOWAS region. The study considered real sector as a combination of the agricultural and manufacturing sectors productivity. Infrastructural development was measured by access to electricity, ICT services, transport, water resources and agricultural land. Evidence from this study supports the

proposition that improving levels of infrastructural development promotes the productivity of the real sector in the region.

For agricultural sector development in the ECOWAS region, this study supports the argument that infrastructural development in the form of ICT, water resources and agricultural land bring about improvements in that sector. All efforts which significantly and positively affect the agricultural sectors productively and employment should be supported and improved upon. This done, the ECOWAS region will be able to compete adequately in the international market given the innovations occasioned by infrastructural development in the agricultural value chain.

No doubt manufacturing sector productivity has remained abysmal in the ECOWAS region. This is not unconnected with the lack and decline of infrastructure in the region. The situation becomes more glaring when the region's infrastructural levels and manufacturing sector productivity are compared with those of Southern African Economic Community. The situation from ECOWAS region further reiterates the argument that it is imperative to design a regional policy that improves physical infrastructure as well as creating manufacturing sector employment for the sustainable development of the manufacturing sector.

5.4 Recommendations

Based on the findings of this research work, the researcher makes the following recommendations:

Policy makers, leaders and Governments in the ECOWAS region need to galvanize and coordinate efforts at the regional level towards enhancing real sector performance given the role regional infrastructure plays. This has become imperative since the results indicate a positive relationship between infrastructural development and real sector performance. Consequently,

leaders and policy makers should work in unity towards solving the regions infrastructural deficits. Governments of the member countries should explore private-public-partnership (PPP) initiative as a smart means of sourcing for funds to bridge the infrastructure gap in the region. This is intended to fund the building of transport, electricity (power), ICT and other infrastructure that tends to support real and competitive sectors. Specifically, policy makers should as a matter of urgency and necessity develop and implement policies that deepen internet penetration, spread of fixed lines and mobile lines and more importantly increase internet accessibility in the region via 4G or 5G network cables. This has become necessary given the results on the impact of ICT on the real sector performance.

Since the results of this study indicate that infrastructural development is effective in sustainable agricultural productivity, the study recommends that such infrastructures like electricity, transportation, and ICT, water and land area should be channelled towards increasing investments in agriculture. It should be noted that while availability and quality of infrastructure cannot replace efficient macroeconomic and agriculture specific policy guidelines, paucity of infrastructure can be a significant constraint to agricultural sector performance.

Transport infrastructure, access to electricity, ICT, water infrastructure and land area improve employment opportunities in the agricultural sector. This study recommends the stepping up of efforts towards increased investment in these categories of infrastructure in order to ameliorate the unemployment situation in most countries of the region, since infrastructural development exerts positive impact on agricultural employment.

Again, this study recommends increased investment on infrastructural development especially in the manufacturing sector since evidence from this research supports the argument that

infrastructural development, enhances manufacturing sector output as well as increases the number of persons employed in the sector.

FDI inflows impact positively on real sector performance as evidence from this study suggests. Policy makers should endeavour to initiate policies that will enhance FDI inflows into the productive sectors of the economy. Adequate infrastructures are necessary in encouraging FDI inflows, Osabuohien *et al* (2020).

Financial inclusion and financial reforms should be pursued vigorously. The results of this study indicate that it is a significant determinant of real sector performance in the ECOWAS region.

5.5 Contribution to Knowledge

The following constitutes this study's contribution to knowledge;

1. Previous research efforts in this area considered the effect of infrastructure development on either the manufacturing sector or agricultural sector, which is, adopting the disaggregated approach. This study, however, adopted the aggregated and disaggregated approach in determining the impact of infrastructural development on real sector performance. That is, jointly examining the effect of infrastructural development on both agricultural and manufacturing sector performance in the ECOWAS region while taking the real sector to mean a combination of the agricultural and manufacturing sector as well as employment in these sub sectors.
2. In order to allow for robustness and further ensure specific effects of infrastructural development, the study considered five models designed to capture the effects of infrastructural development on aggregated real sector performance, disaggregated agricultural sector performance, agricultural sector employment, disaggregated

manufacturing sector performance and manufacturing sector employment. This is unlike previous studies that employed a single model approach.

3. The study adopted the GMM methodology in estimating the novel infrastructural development real sector nexus in a panel of fifteen ECOWAS countries. Previous studies had earlier examined infrastructural development and its effect on either agricultural sector performance or manufacturing sector performance using other methodologies – Edeme *et al* (2020a) and Umofia *et al* (2018)

5.6 Suggestions for Further Research

This study considered the real sector to mean a combination of the agricultural sector performance and the manufacturing sector performance. Other studies could consider real sector to include Construction and the Service sectors, as well as Trade Openness. Apart from expanding the size of the real sector, considering the aforementioned sectors will broaden the analysis of the effects of infrastructural development on economic performance in the ECOWAS region. Other methodologies could equally be used to verify the findings of this study in an effort to better appreciate the recommendations thereof.

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APPENDIX 2 – Panel Unit Root Test

Panel unit root test: Summary
Series: AGRMAF_GDP
Date: 01/04/23 Time: 01:00
Sample: 2000 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-1.72126	0.0626	15	300
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.16753	0.5665	15	300
ADF - Fisher Chi-square	23.6245	0.7887	15	300
PP - Fisher Chi-square	29.6797	0.4821	15	315

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(AGRMAF_GDP)
Date: 01/04/23 Time: 01:04
Sample: 2000 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-10.0738	0.0000	15	285
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-9.49684	0.0000	15	285
ADF - Fisher Chi-square	143.914	0.0000	15	285
PP - Fisher Chi-square	487.664	0.0000	15	300

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: AGR_GDP
Date: 01/04/23 Time: 01:06
Sample: 2000 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-1.40789	0.0796	15	300
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-0.10476	0.4583	15	300
ADF - Fisher Chi-square	26.7845	0.6346	15	300
PP - Fisher Chi-square	32.8526	0.3290	15	315

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(AGR_GDP)
Date: 01/04/23 Time: 01:07
Sample: 2000 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-13.2636	0.0000	15	285
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-11.4372	0.0000	15	285
ADF - Fisher Chi-square	174.766	0.0000	15	285
PP - Fisher Chi-square	500.553	0.0000	15	300

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: MAF_GDP
Date: 01/04/23 Time: 01:08
Sample: 2000 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-2.70864	0.0034	15	300
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-1.89647	0.0289	15	300
ADF - Fisher Chi-square	47.0784	0.0244	15	300
PP - Fisher Chi-square	40.9592	0.0476	15	315

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: EMPLOY_AGR
Date: 01/04/23 Time: 01:12
Sample: 2000 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-1.17411	0.2108	15	300
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.86578	0.8067	15	300
ADF - Fisher Chi-square	29.8981	0.4709	15	300
PP - Fisher Chi-square	11.1408	0.9993	15	315

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(EMPLOY_AGR)
Date: 01/04/23 Time: 01:13
Sample: 2000 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	5.04138	0.0012	15	285
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-1.22039	0.0112	15	285
ADF - Fisher Chi-square	49.7599	0.0131	15	285
PP - Fisher Chi-square	163.643	0.0000	15	300

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: EMPLOY_MAF
Date: 01/04/23 Time: 01:14
Sample: 2000 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-1.84787	0.0623	15	300
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	1.59475	0.9446	15	300
ADF - Fisher Chi-square	34.0795	0.2777	15	300
PP - Fisher Chi-square	31.7158	0.3809	15	315

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(EMPLOY_MAF)
Date: 01/04/23 Time: 01:15
Sample: 2000 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	2.76026	0.0065	15	285
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-2.39816	0.0082	15	285
ADF - Fisher Chi-square	64.5443	0.0003	15	285
PP - Fisher Chi-square	338.934	0.0000	15	300

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: ELECTinfra
Date: 01/04/23 Time: 01:17
Sample: 2000 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.98758	0.1617	15	300
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	3.63986	0.9999	15	300
ADF - Fisher Chi-square	7.84281	1.0000	15	300
PP - Fisher Chi-square	14.6391	0.9916	15	315

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(ELECTinfra)
Date: 01/04/23 Time: 01:17
Sample: 2000 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-8.94505	0.0000	15	285
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-10.5443	0.0000	15	285
ADF - Fisher Chi-square	160.217	0.0000	15	285
PP - Fisher Chi-square	1444.82	0.0000	15	300

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: TRANSinfra
Date: 01/04/23 Time: 01:18
Sample: 2000 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.33860	0.3675	15	300
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-0.15259	0.4394	15	300
ADF - Fisher Chi-square	34.4279	0.2641	15	300
PP - Fisher Chi-square	34.4413	0.2635	15	315

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(TRANSinfra)
Date: 01/04/23 Time: 01:19
Sample: 2000 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-7.39850	0.0000	15	285
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-8.46452	0.0000	15	285
ADF - Fisher Chi-square	126.686	0.0000	15	285
PP - Fisher Chi-square	325.063	0.0000	15	300

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: ICTinfra
Date: 01/04/23 Time: 01:19
Sample: 2000 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-1.83537	0.0632	15	300
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	1.90239	0.9714	15	300
ADF - Fisher Chi-square	15.9689	0.9830	15	300
PP - Fisher Chi-square	18.3075	0.9533	15	315

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(ICTinfra)
Date: 01/04/23 Time: 01:20
Sample: 2000 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-2.85999	0.0021	15	285
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-3.70070	0.0001	15	285
ADF - Fisher Chi-square	61.8882	0.0005	15	285
PP - Fisher Chi-square	357.746	0.0000	15	300

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: WATERinfra
Date: 01/04/23 Time: 01:21
Sample: 2000 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-5.50822	0.0000	14	280
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-6.53889	0.0000	14	280
ADF - Fisher Chi-square	121.397	0.0000	14	280
PP - Fisher Chi-square	212.450	0.0000	14	294

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: AGRICinfra
Date: 01/04/23 Time: 01:22
Sample: 2000 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-3.26778	0.0005	15	300
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-2.28870	0.0110	15	300
ADF - Fisher Chi-square	48.6066	0.0172	15	300
PP - Fisher Chi-square	73.6444	0.0000	15	315

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: CU
Date: 01/04/23 Time: 01:23
Sample: 2000 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.67980	0.2483	15	300
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	3.23996	0.9994	15	300
ADF - Fisher Chi-square	10.5768	0.9996	15	300
PP - Fisher Chi-square	9.48204	0.9999	15	315

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(CU)
Date: 01/04/23 Time: 01:24
Sample: 2000 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-11.1533	0.0000	15	285
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-10.5770	0.0000	15	285
ADF - Fisher Chi-square	159.137	0.0000	15	285
PP - Fisher Chi-square	231.445	0.0000	15	300

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: FDI
Date: 01/04/23 Time: 01:24
Sample: 2000 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-1.58083	0.0470	15	300
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-2.32839	0.0099	15	300
ADF - Fisher Chi-square	49.7632	0.0131	15	300
PP - Fisher Chi-square	62.3738	0.0005	15	315

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: FSD
Date: 01/04/23 Time: 01:25
Sample: 2000 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-1.24790	0.1060	15	300
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.80711	0.7902	15	300
ADF - Fisher Chi-square	25.3043	0.7101	15	300
PP - Fisher Chi-square	18.1468	0.9561	15	315

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(FSD)
Date: 01/04/23 Time: 01:26
Sample: 2000 2021
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-6.15022	0.0000	15	285
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-7.45397	0.0000	15	285
ADF - Fisher Chi-square	111.420	0.0000	15	285
PP - Fisher Chi-square	222.369	0.0000	15	300

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

APPENDIX 3 – PEDRONI COINTERGRATION TEST

Pedroni Residual Cointegration Test
Series: AGRMAF_GDP ICTinfra ELECTinfra WATERinfra AGRICinfra CU FDI FSD EMPLOY_AGR EMPLOY_MAF
Date: 01/04/23 Time: 01:53
Sample: 2000 2021
Included observations: 330
Cross-sections included: 14 (1 dropped)
Null Hypothesis: No cointegration
Trend assumption: No deterministic trend
User-specified lag length: 1
Newey-West automatic bandwidth selection and Bartlett kernel

Alternative hypothesis: common AR coefs. (within-dimension)

	Statistic	Prob.	Weighted Statistic	Prob.
Panel v-Statistic	3.275761	0.0014	-4.292277	0.0000
Panel rho-Statistic	3.910738	0.0001	4.705448	0.0000
Panel PP-Statistic	-3.925181	0.0000	-5.253938	0.0000
Panel ADF-Statistic	-5.841543	0.0000	-4.704920	0.0000

Alternative hypothesis: individual AR coefs. (between-dimension)

	Statistic	Prob.
Group rho-Statistic	3.643187	0.0001
Group PP-Statistic	-6.707238	0.0000
Group ADF-Statistic	-3.581836	0.0002

Cross section specific results

Phillips-Peron results (non-parametric)

Cross ID	AR(1)	Variance	HAC	Bandwidth	Obs
1	0.118	0.539356	0.539356	0.00	21
2	-0.036	1.283049	1.285693	1.00	21
3	0.339	0.715061	0.715061	0.00	21
4	0.147	4.956650	2.710941	4.00	21
5	-0.457	1.788673	1.823461	1.00	21
6	0.227	4.286513	0.657178	10.00	21
7	-0.002	0.741049	0.741049	0.00	21
8	Dropped from Test				
9	0.389	8.810692	6.936529	3.00	21
10	0.143	1.393027	0.878336	4.00	21
11	0.014	2.221309	2.221309	0.00	21
12	0.378	7.786275	9.025837	2.00	21
13	0.381	0.874273	0.743674	1.00	21
14	0.196	8.053459	8.053459	0.00	21
15	0.025	9.258668	0.832675	20.00	21

Augmented Dickey-Fuller results (parametric)

Cross ID	AR(1)	Variance	Lag	Max lag	Obs
1	0.202	0.547242	1	--	20
2	0.065	1.259846	1	--	20
3	0.314	0.500569	1	--	20
4	-0.081	4.825746	1	--	20
5	-0.405	1.874838	1	--	20
6	-0.231	2.937556	1	--	20
7	0.034	0.767527	1	--	20
8		Dropped from Test			
9	0.021	6.193156	1	--	20
10	-0.122	1.146572	1	--	20
11	-0.014	2.261177	1	--	20
12	-0.033	4.749423	1	--	20
13	0.419	0.806091	1	--	20
14	0.206	6.379693	1	--	20
15	-0.481	6.767674	1	--	20

APPENDIX 4 – SHORT RUN COEFFICIENT

MODEL 1: REAL SECTOR OUTPUT MODEL (AGRMAF_GDP)

Dependent Variable: AGRMAF_GDP
Method: Panel Generalized Method of Moments
Transformation: First Differences
Date: 01/04/23 Time: 05:27
Sample (adjusted): 2002 2020
Periods included: 19
Cross-sections included: 15
Total panel (balanced) observations: 285
White period instrument weighting matrix
White period standard errors & covariance (d.f. corrected)
Instrument specification: @DYN(AGRMAF_GDP,-2)EMPLOY_AGR(1)
EMPOLY_MAF(1)
ELECTINF(1) TRANSINF(1) ICTINF(1) WATERINF(1) AGRICINF(1)
CU(1) FDI(1) FSD(1)
Constant added to instrument list

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AGRMAF_GDP (-1)	0.247686	0.107926	2.294961	0.0015
EMPLOY_AGR	6.164643	2.451131	2.515019	0.0012
EMPOLY_MAF	3.990856	1.106170	3.607814	0.0000
ELECTINF	0.299216	0.821672	0.364155	0.7160
TRANSINF	14.40374	53.00420	0.271747	0.7860
ICTINF	0.000575	0.000732	0.785582	0.4328
WATERINF	8.768990	27.09795	0.323603	0.7465
AGRICINF	0.073278	1.302165	0.056274	0.9552
CU	-0.005577	0.002162	-2.579555	0.0009
FDI	0.155576	0.487005	0.319455	0.7496
FSD	1.859841	3.824527	0.486293	0.6271

Effects Specification

Cross-section fixed (first differences)

Mean dependent var	-0.304194	S.D. dependent var	3.063282
S.E. of regression	8.565218	Sum squared resid	20101.45
J-statistic	5.024286	Instrument rank	15
Prob(J-statistic)	0.284815		

Dependent Variable: AGRMAF_GDP
Method: Panel Generalized Method of Moments
Transformation: Orthogonal Deviations
Date: 01/04/23 Time: 05:30
Sample (adjusted): 2002 2020
Periods included: 19
Cross-sections included: 15
Total panel (balanced) observations: 285
White period instrument weighting matrix
White period standard errors & covariance (d.f. corrected)
Instrument specification: @DYN(AGRMAF_GDP,-2)EMPLOY_AGR(1)
EMPOLY_MAF(1)

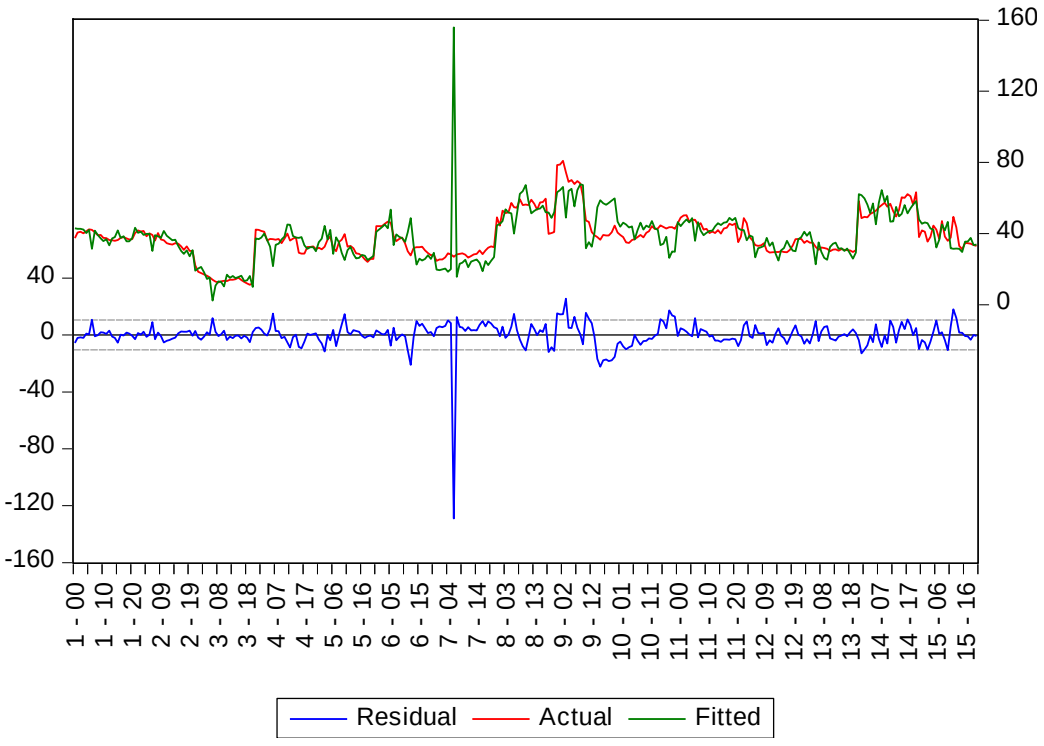
ELECTINF(1) TRANSINF(1) ICTINF(1) WATERINF(1) AGRICINF(1)
CU(1) FDI(1) FSD(1)
Constant added to instrument list

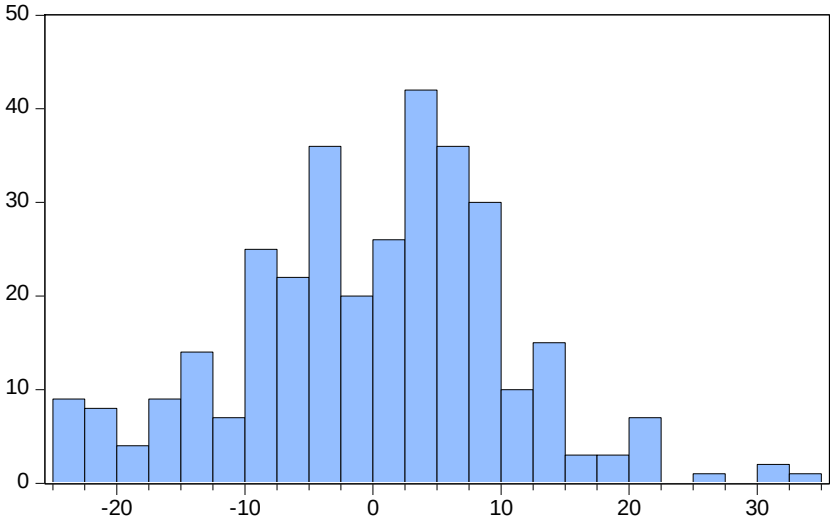
Variable	Coefficient	Std. Error	t-Statistic	Prob.
AGRMAF_GDP(-1)	0.661929	0.266632	2.482557	0.0136
EMPLOY_AGR	-0.644302	1.544837	-0.417068	0.6770
EMPLOY_MAF	1.813080	3.844449	0.471610	0.6376
ELECTINF	0.155371	0.722818	0.214952	0.8300
TRANSINF	-28.13777	30.50286	-0.922463	0.3571
ICTINF	-0.004092	0.014713	-0.278117	0.7811
WATERINF	-4.900109	9.374317	-0.522716	0.6016
AGRICINF	0.412884	0.853208	0.483919	0.6288
CU	3.35E-10	9.20E-10	0.364492	0.7158
FDI	0.031707	0.184033	0.172290	0.8633
FSD	-0.726821	1.833280	-0.396459	0.6921

Effects Specification

Cross-section fixed (orthogonal deviations)

Mean dependent var	1.986718	S.D. dependent var	5.479317
S.E. of regression	15.47725	Sum squared resid	65635.39
J-statistic	6.253005	Instrument rank	15
Prob(J-statistic)	0.181034		





Series: Standardized Residuals
Sample 2000 2021
Observations 330

Mean	-5.89e-15
Median	1.396749
Maximum	32.92772
Minimum	-24.54677
Std. Dev.	10.51455
Skewness	-0.067118
Kurtosis	3.176536
Jarque-Bera	0.676280
Probability	0.713095

Arellano-Bond Serial Correlation Test
Equation: Untitled
Date: 01/04/23 Time: 05:32
Sample: 2000 2021
Included observations: 285

Test order	m-Statistic	rho	SE(rho)	Prob.
AR(1)	0.050015	4048.369064	80943.65062	0.9601
AR(2)	0.024103	2443.342369	101369.9067	0.9808

MODEL 2: AGRIC SECTOR VALUE ADDED MODEL

Dependent Variable: AGR_GDP
Method: Panel Generalized Method of Moments
Transformation: First Differences
Date: 01/04/23 Time: 05:44
Sample (adjusted): 2002 2020
Periods included: 19
Cross-sections included: 15
Total panel (balanced) observations: 285
White period instrument weighting matrix
White period standard errors & covariance (d.f. corrected)
Instrument specification: @DYN(AGR_GDP,-2) EMPLOY_AGR(1) ELECTINF(1) TRANSINF(1) ICTINF(1) WATERINF(1) AGRICINF(1) CU(1) FDI(1) FSD(1)
Constant added to instrument list

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AGR_GDP	0.918288	0.191290	4.800509	0.0000
EMPLOY_AGR	2.671961	2.777490	0.962006	0.3369
ELECTINF	0.208691	0.374669	0.557003	0.5780
TRANSINF	2.477727	13.81114	0.179401	0.8578
ICTINF	0.000399	0.000548	0.728376	0.4670
WATERINF	14.38526	9.998033	1.438809	0.1513
AGRICINF	0.431065	0.919026	0.469046	0.6394
CU	4.03E-11	5.18E-10	0.077867	0.9380
FDI	-0.254219	0.219949	-1.155809	0.2488
FSD	0.898468	1.935726	0.464151	0.6429

Effects Specification

Cross-section fixed (first differences)

Mean dependent var	-0.259993	S.D. dependent var	3.045108
S.E. of regression	7.592671	Sum squared resid	15853.38
J-statistic	5.180905	Instrument rank	15
Prob(J-statistic)	0.394204		

Dependent Variable: AGR_GDP

Method: Panel Generalized Method of Moments
Transformation: Orthogonal Deviations
Date: 01/04/23 Time: 05:50
Sample (adjusted): 2002 2020
Periods included: 19

Arellano-Bond Serial Correlation Test
Equation: Untitled
Date: 01/04/23 Time: 11:51
Sample: 2000 2021
Included observations: 300

Cross-sections included: 15
Total panel (balanced) observations: 285
White period instrument weighting matrix
White period standard errors & covariance (d.f. corrected)
Instrument specification: @DYN(AGRIC,-2) EMPLOY_AGR(1) ELECTINF(1) TRANSINF(1) ICTINF(1) WATERINF(1) AGRICINF(1) CU(1) FDI(1) FSD(1)
Constant added to instrument list

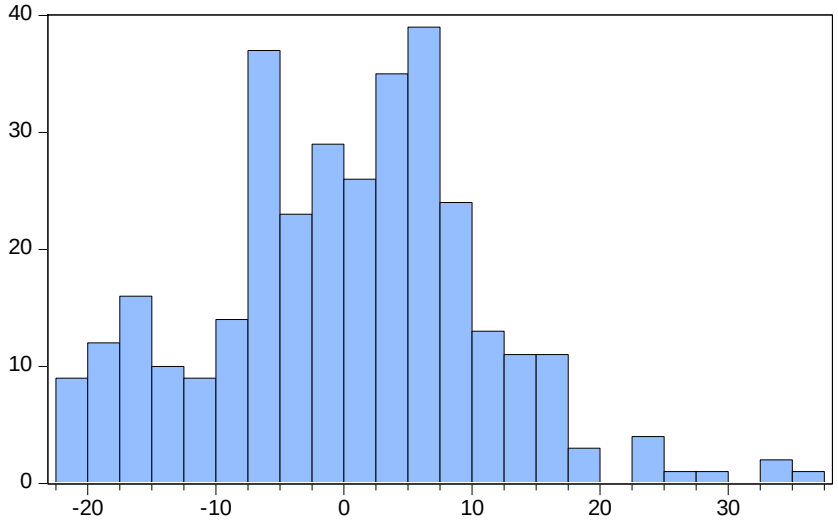
Variable	Coefficient	Std. Error	t-Statistic	Prob.
AGR_GDP	0.703685	0.199864	3.520825	0.0005
EMPLOY_AGR	-0.182290	1.174274	-0.155236	0.8767
ELECTINF	0.169308	0.476612	0.355233	0.7227
TRANSINF	-17.56538	20.66249	-0.850110	0.3960
ICTINF	-0.009983	0.015924	-0.626933	0.5312
WATERINF	-0.445875	5.028002	-0.088678	0.9294
AGRICINF	0.424214	0.629791	0.673578	0.5011
CU	-2.45E-11	2.02E-10	-0.121301	0.9035
FDI	-0.118329	0.097962	-1.207907	0.2281
FSD	-0.073977	0.970322	-0.076239	0.9393

Effects Specification

Cross-section fixed (orthogonal deviations)

Mean dependent var	1.748398	S.D. dependent var	5.374644
S.E. of regression	29.57879	Sum squared resid	240598.8
J-statistic	3.214577	Instrument rank	15
Prob(J-statistic)	0.666943		

Test order	m-Statistic	rho	SE(rho)	Prob.
AR(1)	-0.311274	-85.498058	274.671619	0.7556
AR(2)	-1.281690	-524.858262	409.504695	0.2000



Series: Standardized Residuals
Sample 2000 2021
Observations 330

Mean	-6.30e-16
Median	0.521728
Maximum	36.17283
Minimum	-22.06215
Std. Dev.	10.61498
Skewness	0.186460
Kurtosis	3.307665
Jarque-Bera	3.213736
Probability	0.200515

Model 3: Agric. Sector Employment Model

Dependent Variable: EMPLOY_AGR
Method: Panel Generalized Method of Moments
Transformation: First Differences
Date: 01/04/23 Time: 12:17
Sample (adjusted): 2002 2020
Periods included: 19
Cross-sections included: 15
Total panel (balanced) observations: 285
White period instrument weighting matrix
White period standard errors & covariance (d.f. corrected)
Instrument specification: @DYN(EMPLOY_AGR,-2) ELECTINF(1) TRANSINF(1) ICTINF(1) WATERINF(1) AGRICINF(1) CU(1) FDI(1) FSD(1)
Constant added to instrument list

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMPLOY_AGR(-1)	0.792171	0.222242	3.564456	0.0004
ELECTINF	-0.014071	0.029475	-0.477377	0.6335
TRANSINF	-1.127133	1.424247	-0.791389	0.4294
ICTINF	4.11E-05	4.21E-05	0.975773	0.3300
WATERINF	-0.064126	0.482003	-0.133041	0.8943
AGRICINF	-0.075371	0.078853	-0.955841	0.3400
CU	-3.71E-10	3.89E-10	-0.954106	0.3409
FDI	-0.032232	0.032893	-0.979899	0.3280
FSD	-0.020810	0.094697	-0.219748	0.8262

Effects Specification

Cross-section fixed (first differences)

Mean dependent var	-0.726070	S.D. dependent var	0.963573
S.E. of regression	1.074916	Sum squared resid	318.9025
J-statistic	9.944444	Instrument rank	16
Prob(J-statistic)	0.061165		

Dependent Variable: EMPLOY_AGR
Method: Panel Generalized Method of Moments
Transformation: Orthogonal Deviations
Date: 01/04/23 Time: 12:21
Sample (adjusted): 2002 2020
Periods included: 19
Cross-sections included: 15
Total panel (balanced) observations: 285
White period instrument weighting matrix
White period standard errors & covariance (d.f. corrected)
Instrument specification: @DYN(EMPLOY_AGR,-2) ELECTINF(1) TRANSINF(1) ICTINF(1) WATERINF(1) AGRICINF(1) CU(1) FDI(1)
Constant added to instrument list

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMPLOY_AGR(-1)	0.977720	0.084264	11.60309	0.0000

ELECTINF	-0.023167	0.017409	-1.330721	0.1844
TRANSINF	2.114348	4.178741	0.505977	0.6133
ICTINF	0.000223	0.001563	0.142748	0.8866
WATERINF	-0.215450	0.384505	-0.560329	0.5757
AGRICINF	0.008830	0.069077	0.127833	0.8984
CU	-1.63E-11	2.32E-10	-0.070492	0.9439
FDI	0.024642	0.036136	0.681928	0.4959
FSD	-0.052775	0.090232	-0.584879	0.5591

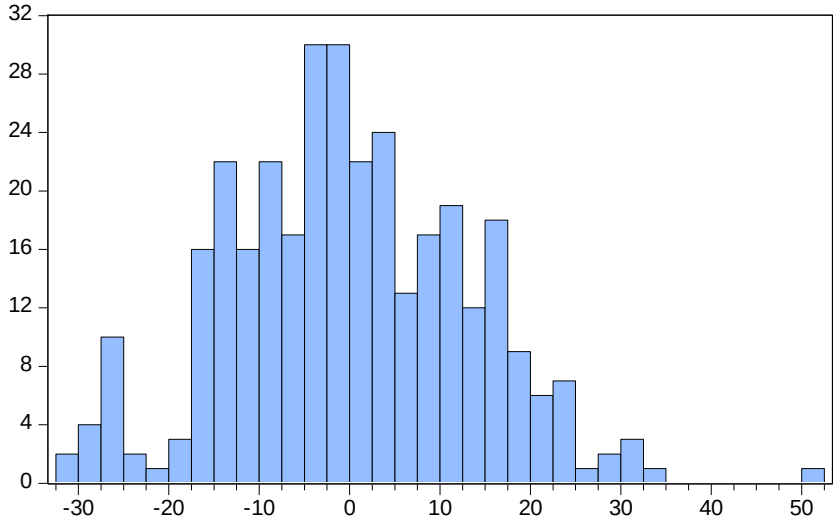
Effects Specification

Cross-section fixed (orthogonal deviations)

Mean dependent var	4.258784	S.D. dependent var	4.927409
S.E. of regression	1.209368	Sum squared resid	403.6699
J-statistic	5.229210	Instrument rank	15
Prob(J-statistic)	0.514769		

Arellano-Bond Serial Correlation Test
Equation: Untitled
Date: 01/04/23 Time: 12:15
Sample: 2000 2021
Included observations: 300

Test order	m-Statistic	rho	SE(rho)	Prob.
AR(1)	1.058181	96.816873	138.910605	0.3902
AR(2)	0.742424	47.088230	153.634392	0.2061



Series: Standardized Residuals	
Sample 2000 2021	
Observations 330	
Mean	9.37e-15
Median	-0.859918
Maximum	50.08887
Minimum	-31.27033
Std. Dev.	13.31940
Skewness	0.171080
Kurtosis	3.081687
Jarque-Bera	1.701502
Probability	0.427094

Model 4: Manufacturing Sector Output Model

Dependent Variable: MAF_GDP
Method: Panel Generalized Method of Moments
Transformation: First Differences
Date: 01/04/23 Time: 13:38
Sample (adjusted): 2001 2020
Periods included: 20
Cross-sections included: 15
Total panel (balanced) observations: 300
Difference specification instrument weighting matrix
White period standard errors & covariance (d.f. corrected)
Instrument specification: MAF_GDP(1) ELECTINF(1) TRANSINF(1) ICTINF(1) WATERINF(1) AGRICINF(1) CU(1) FDI(1) FSD(1)
Constant added to instrument list

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MAF_GDP	0.320849	0.409959	0.782636	0.4345
ELECTINF	0.006952	0.075420	0.092179	0.9266
TRANSINF	0.032093	1.403280	0.022870	0.9818
ICTINF	0.000103	1.94E-05	5.301284	0.0000
WATERINF	0.921623	0.558606	1.649863	0.1000
AGRICINF	0.380169	0.176866	2.149477	0.0324
CU	6.88E-11	4.60E-11	1.495700	0.1358
FDI	0.010719	0.022083	0.485386	0.6278
FSD	0.092263	0.356582	0.258742	0.7960

Effects Specification

Cross-section fixed (first differences)

Mean dependent var	-0.053325	S.D. dependent var	1.084936
S.E. of regression	1.173259	Sum squared resid	400.5720
J-statistic	5.607329	Instrument rank	9
Prob(J-statistic)	0.617762		

Arellano-Bond Serial Correlation Test
Equation: Untitled
Date: 01/04/23 Time: 13:41
Sample: 2000 2021
Included observations: 300

Test order	m-Statistic	rho	SE(rho)	Prob.
AR(1)	0.345518	8.100506	23.444498	0.7297
AR(2)	-0.279763	-12.030644	43.003051	0.7797

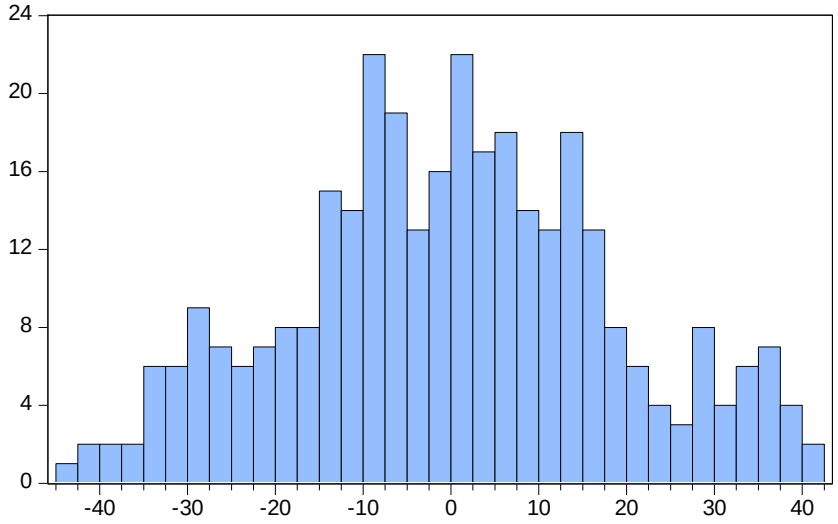
Dependent Variable: MAF_GDP
Method: Panel Generalized Method of Moments
Transformation: First Differences
Date: 01/05/23 Time: 12:59
Sample (adjusted): 2002 2020
Periods included: 19
Cross-sections included: 15
Total panel (balanced) observations: 285
White period instrument weighting matrix
White period standard errors & covariance (d.f. corrected)
Instrument specification: @DYN(MAF_GDP,-2) EMPLOY_MAF(1) ELECTINF(1) TRANSINF(1) ICTINF(1) WATERINF(1) AGRICINF(1) CU(1) FDI(1) FSD(1)
Constant added to instrument list

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MAF_GDP(-1)	0.146343	0.871283	0.167962	0.8667
EMPLOY_MAF	-0.399387	1.213782	-0.329043	0.7424
ELECTINF	0.213208	0.257047	0.829449	0.4076
TRANSINF	-1.131964	7.964076	-0.142134	0.8871
ICTINF	0.000115	6.11E-05	1.882896	0.0608
WATERINF	-1.137702	2.114619	-0.538017	0.5910
AGRICINF	0.025330	0.365701	0.069265	0.9448
CU	-6.33E-10	6.82E-10	-0.927641	0.3544
FDI	-0.251692	0.473438	-0.531627	0.5954
FSD	0.026110	0.184736	0.141335	0.8877

Effects Specification

Cross-section fixed (first differences)

Mean dependent var	-0.044201	S.D. dependent var	1.096656
S.E. of regression	2.784210	Sum squared resid	2131.751
J-statistic	2.779466	Instrument rank	15
Prob(J-statistic)	0.733940		



Series: Standardized Residuals	
Sample 2000 2021	
Observations 330	
Mean	-2.27e-14
Median	0.150851
Maximum	40.52276
Minimum	-44.68431
Std. Dev.	18.37180
Skewness	0.050948
Kurtosis	2.621183
Jarque-Bera	2.115925
Probability	0.347162

Model 5: Manufacturing Sector Employment Model

Dependent Variable: EMPLOY_MAF
Method: Panel Generalized Method of Moments
Transformation: First Differences
Date: 01/05/23 Time: 13:22
Sample (adjusted): 2002 2020
Periods included: 19
Cross-sections included: 15
Total panel (balanced) observations: 285
White period instrument weighting matrix
White period standard errors & covariance (d.f. corrected)
Instrument specification: @DYN(EMPLOY_MAF,-2) ELECTINF(1) TRANSINF(1) ICTINF(1) WATERINF(1) AGRICINF(1) CU(1) FDI(1) FSD(1)
Constant added to instrument list

Variable	Coefficient	Std. Error	t-Statistic	Prob.
EMPLOY_MAF(-1)	0.904369	0.114807	7.877310	0.0000
ELECTINF	-0.002905	0.023989	-0.121078	0.9037
TRANSINF	0.962585	1.620337	0.594064	0.5530
ICTINF	1.47E-05	1.54E-05	0.958450	0.3387
WATERINF	0.107298	0.088117	1.217683	0.2244
AGRICINF	0.025320	0.042272	0.598981	0.5497
CU	-1.45E-10	1.47E-10	-0.984350	0.3258
FDI	0.000718	0.004427	0.162218	0.8713
FSD	0.019022	0.038241	0.497417	0.6193

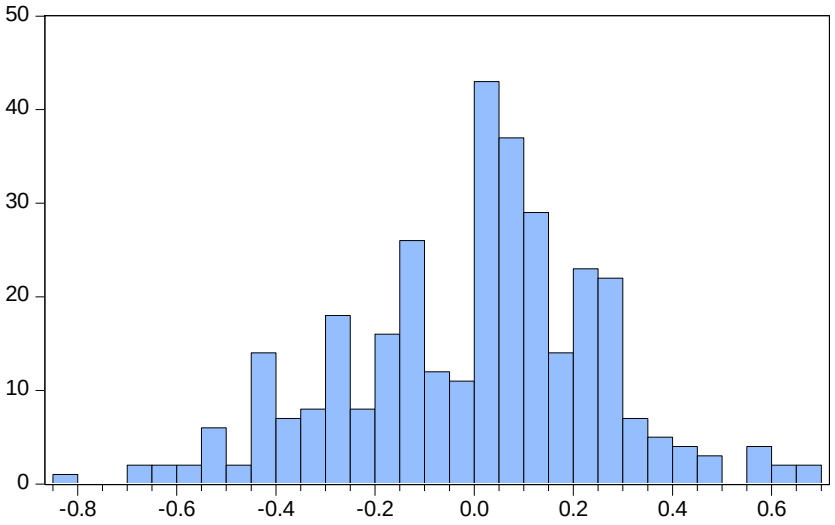
Effects Specification

Cross-section fixed (first differences)

Mean dependent var	0.139489	S.D. dependent var	0.619779
S.E. of regression	0.590382	Sum squared resid	96.19996
J-statistic	6.129481	Instrument rank	16
Prob(J-statistic)	0.524715		

Arellano-Bond Serial Correlation Test
Equation: Untitled
Date: 01/05/23 Time: 13:25
Sample: 2000 2021
Included observations: 300

Test order	m-Statistic	rho	SE(rho)	Prob.
AR(1)	1.609040	73.041131	45.394237	0.1076
AR(2)	1.123218	41.240815	36.716670	0.2613



Series: Standardized Residuals
Sample 2000 2021
Observations 330

Mean	6.05e-16
Median	0.044028
Maximum	0.669408
Minimum	-0.820501
Std. Dev.	0.258546
Skewness	-0.279924
Kurtosis	3.101817
Jarque-Bera	4.452196
Probability	0.107949

APPENDIX 5 - Long run coefficients

Model 1: REAL SECTOR OUTPUT MODEL

EMPLOY_AGR

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	2.432247	273	0.0008
F-statistic	14.29476	(1, 273)	0.0000
Chi-square	7.929476	1	0.0000

Null Hypothesis: C(2) = C(1)/ (1 - C(2))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(2) - C(1)/(1 - C(2))	0.417579	0.171685

Delta method computed using analytic derivatives.

EMPLOY_MAF

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	1.901706	273	0.0113
F-statistic	9.064112	(1, 273)	0.0113
Chi-square	7.064112	1	0.0071

Null Hypothesis: C(3) = C(1) / (1 - C(3))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(3) - C(1)/(1 - C(3))	0.291349	0.153204

Delta method computed using analytic derivatives.

ELECTINF

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	2.534012	273	0.0000
F-statistic	9.315047	(1, 273)	0.0000
Chi-square	6.315047	1	0.0015

Null Hypothesis: C(4) = C(1) / (1 - C(4))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(4) - C(1)/(1 - C(4))	2.905891	1.146755

Delta method computed using analytic derivatives.

TRANSINF

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	2.893309	273	0.0000
F-statistic	9.041163	(1, 273)	0.0000
Chi-square	6.041163	1	0.0002

Null Hypothesis: C(5) = C(1) / (1 - C(5))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(5) - C(1)/(1 - C(5))	0.967870	0.334520

Delta method computed using analytic derivatives.

ICTINF

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	7.863738	273	0.0000
F-statistic	6.092079	(1, 273)	0.0000
Chi-square	5.092079	1	0.0016

Null Hypothesis: C(6) = C(1) / (1 - C(6))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(6) - C(1)/(1 - C(6))	2.386209	0.303445

Delta method computed using analytic derivatives.

WATERINF

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	0.544016	273	0.5869
F-statistic	0.295953	(1, 273)	0.5869
Chi-square	0.295953	1	0.5864

Null Hypothesis: C(7) = C(1) / (1- C(7))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(7) - C(1)/(1 - C(7))	0.067431	0.123950

Delta method computed using analytic derivatives.

CU

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	-0.506146	273	0.6132
F-statistic	0.256184	(1, 273)	0.6132
Chi-square	0.256184	1	0.6128

Null Hypothesis: C(8) = (1 - C(8))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
-1 + 2*C(8)	-4.243763	8.384466

Restrictions are linear in coefficients.

FDI

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	3.803328	273	0.0000
F-statistic	3.144647	(1, 273)	0.0000
Chi-square	3.144647	1	0.0037

Null Hypothesis: C(9) = C(1) /(1 - C(9))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(9) - C(1)/(1 - C(9))	0.156313	0.041099

Delta method computed using analytic derivatives.

FSD

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	2.795589	273	0.0000
F-statistic	7.293459	(1, 273)	0.0000
Chi-square	6.293459	1	0.0000

Null Hypothesis: C(10) = C(1) / (1 - C(10))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(10) - C(1)/(1 - C(10))	0.067192	0.024035

Delta method computed using analytic derivatives.

Model 2: AGRIC SECTOR OUTPUT MODEL

EMPLOY_AGR

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	1.992721	275	0.0439
F-statistic	2.825045	(1, 275)	0.0439
Chi-square	2.825045	1	0.0428

Null Hypothesis: C(2) = C(1)/(1-C(2))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(2) - C(1)/(1 - C(2))	3.221189	1.616477

Delta method computed using analytic derivatives.

ELECTINF

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	3.866233	275	0.0001
F-statistic	14.94776	(1, 275)	0.0001
Chi-square	14.94776	1	0.0001

Null Hypothesis: C(3) = C(1) / (1- C(3))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(3) - C(1)/(1 - C(3))	0.968429	0.250484

Delta method computed using analytic derivatives.

TRANSINF

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	12.76792	275	0.0000
F-statistic	9.046113	(1, 275)	0.0000
Chi-square	9.046113	1	0.0000

Null Hypothesis: C(4) = C(1) / (1- C(4))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(4) - C(1)/(1 - C(4))	2.741776	0.214739

Delta method computed using analytic derivatives.

ICTINF

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	4.802797	275	0.0000
F-statistic	23.06686	(1, 275)	0.0000
Chi-square	23.06686	1	0.0000

Null Hypothesis: C(5) = C(1) / (1 - C(5))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(5) - C(1)/(1 - C(5))	0.918321	0.191205

Delta method computed using analytic derivatives.

WATERINF

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	9.956432	275	0.0000
F-statistic	8.107467	(1, 275)	0.0000
Chi-square	8.107467	1	0.0000

Null Hypothesis: C(6) = C(1) / (1 - C(6))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(6) - C(1)/(1 - C(6))	14.45387	1.451712

Delta method computed using analytic derivatives.

AGRICINF

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	1.891495	275	0.0674
F-statistic	2.529694	(1, 275)	0.0674
Chi-square	2.529694	1	0.0667

Null Hypothesis: C(7) = C(1) / (1 - C(7))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(7) - C(1)/(1 - C(7))	1.182983	0.625422

Delta method computed using analytic derivatives.

CU

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	4.800509	275	0.0000
F-statistic	23.04489	(1, 275)	0.0000
Chi-square	23.04489	1	0.0000

Null Hypothesis: C(8) = C(1) / (1 - C(8))

Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(8) - C(1)/(1 - C(8))	0.918288	0.191290

Delta method computed using analytic derivatives.

FDI

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	4.676638	275	0.0000
F-statistic	21.87095	(1, 275)	0.0000
Chi-square	21.87095	1	0.0000

Null Hypothesis: C(9) = C(1) / (1 - C(9))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(9) - C(1)/(1 - C(9))	0.986378	0.210916

Delta method computed using analytic derivatives.

FSD

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	-0.047412	275	0.9622
F-statistic	0.002248	(1, 275)	0.9622
Chi-square	0.002248	1	0.9622

Null Hypothesis: C(10) = C(1) / (1 - C(10))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(10) - C(1)/(1 - C(10))	-8.145898	171.8095

Delta method computed using analytic derivatives.

MODEL 3: AGRIC EMPLOYMENT MODEL

ELECTINF

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	3.714037	276	0.0002
F-statistic	13.79407	(1, 276)	0.0002
Chi-square	13.79407	1	0.0002

Null Hypothesis: C(2) = C(1) / (1 - C(2))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(2) - C(1)/(1 - C(2))	0.795250	0.214120

Delta method computed using analytic derivatives.

TRANSINF

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	2.158270	276	0.0205
F-statistic	7.575202	(1, 276)	0.0205
Chi-square	7.575202	1	0.0095

Null Hypothesis: C(3) = C(1) / (1 - C(3))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(3) - C(1)/(1 - C(3))	1.499545	0.694790

Delta method computed using analytic derivatives.

ICTINF

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	3.564301	276	0.0004
F-statistic	12.70424	(1, 276)	0.0004
Chi-square	12.70424	1	0.0004

Null Hypothesis: C(4) = C(1) / (1 - C(4))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(4) - C(1)/(1 - C(4))	0.792162	0.222249

Delta method computed using analytic derivatives.

WATERINF

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	0.252939	276	0.8005
F-statistic	0.063978	(1, 276)	0.8005
Chi-square	0.063978	1	0.8003

Null Hypothesis: C(5) = C(1) / (1- (5))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(1)/4 + C(5)	0.133917	0.529443

Restrictions are linear in coefficients.

AGRICINF

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	3.591856	276	0.0004
F-statistic	12.90143	(1, 276)	0.0004
Chi-square	12.90143	1	0.0003

Null Hypothesis: C(6) = C(1) / (1 - C(6))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(6) - C(1)/(1 - C(6))	0.812020	0.226072

Delta method computed using analytic derivatives.

CU

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	3.564456	276	0.0004
F-statistic	12.70534	(1, 276)	0.0004
Chi-square	12.70534	1	0.0004

Null Hypothesis: C(7) = C(1) / (1 - C(7))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(7) - C(1)/(1 - C(7))	0.792171	0.222242

Delta method computed using analytic derivatives.

FDI

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	3.782864	276	0.0002
F-statistic	14.31006	(1, 276)	0.0002
Chi-square	14.31006	1	0.0002

Null Hypothesis: C(8) = C(1) / (1 - C(8))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(8) - C(1)/(1 - C(8))	0.799667	0.211392

Delta method computed using analytic derivatives.

FSD

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	3.959572	276	0.0001
F-statistic	15.67821	(1, 276)	0.0001
Chi-square	15.67821	1	0.0001

Null Hypothesis: C(9) = C(1) / (1-C(9))

Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(9) - C(1)/(1 - C(9))	0.796832	0.201242

Delta method computed using analytic derivatives.

MODEL 4: MANUFACTURING OUTPUT MODEL

EMPLOY_MAF

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	2.212780	275	0.0244
F-statistic	7.124593	(1, 275)	0.0244
Chi-square	7.124593	1	0.0241

Null Hypothesis: C(2) = C(1) / (1 - C(2))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(2) - C(1)/(1 - C(2))	0.503963	0.227751

Delta method computed using analytic derivatives.

ELECTINF

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	2.712491	275	0.0001
F-statistic	9.000454	(1, 275)	0.0001
Chi-square	9.000454	1	0.0001

Null Hypothesis: C(3) = C(1) / (1-C(3))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(3) - C(1)/(1 - C(3))	0.027209	0.010031

Delta method computed using analytic derivatives.

TRANSINF

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	7.355974	275	0.0000
F-statistic	10.026639	(1, 275)	0.0000
Chi-square	10.026639	1	0.0000

Null Hypothesis: C(4) = C(1) / (1 - C(4))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(4) - C(1)/(1 - C(4))	1.200606	0.163215

Delta method computed using analytic derivatives.

ICTINF

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	2.049670	275	0.0368
F-statistic	6.028169	(1, 275)	0.0368
Chi-square	6.028169	1	0.0367

Null Hypothesis: C(5) = C(1) / (1 - C(5))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(5) - C(1)/(1 - C(5))	0.146244	0.071350

Delta method computed using analytic derivatives.

WATERINF

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	-0.647182	275	0.5181
F-statistic	0.418845	(1, 275)	0.5181
Chi-square	0.418845	1	0.5175

Null Hypothesis: C(6) = C(1) / (1 - C(6))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(6) - C(1)/(1 - C(6))	-1.206160	1.863710

Delta method computed using analytic derivatives.

AGRICINF

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	-0.170900	275	0.8644
F-statistic	0.029207	(1, 275)	0.8644
Chi-square	0.029207	1	0.8643

Null Hypothesis: C(7) = C(1) / (1 - C(7))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(7) - C(1)/(1 - C(7))	-0.124816	0.730341

Delta method computed using analytic derivatives.

CU

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	2.052985	275	0.0467
F-statistic	7.028211	(1, 275)	0.0467
Chi-square	7.028211	1	0.0466

Null Hypothesis: C(8) = C(1) / (1 - C(8))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(8) - C(1)/(1 - C(8))	0.146343	0.071283

Delta method computed using analytic derivatives.

FDI

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	2.984317	275	0.0000
F-statistic	10.632416	(1, 275)	0.0000
Chi-square	10.632416	1	0.0000

Null Hypothesis: C(9) = C(1) / (1- C(9))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(9) - C(1)/(1 - C(9))	0.368608	0.123515

Delta method computed using analytic derivatives.

FSD

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	1.829347	275	0.0690
F-statistic	6.019121	(1, 275)	0.0690
Chi-square	6.019121	1	0.0600

Null Hypothesis: C(10) = C(1) / (1 - C(10))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(10) - C(1)/(1 - C(10))	0.124156	0.067869

Delta method computed using analytic derivatives.

MODEL 5: MANUFACTURING EMPLOYMENT MODEL

ELECTINF

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	7.917511	276	0.0000
F-statistic	62.68698	(1, 276)	0.0000
Chi-square	62.68698	1	0.0000

Null Hypothesis: C(2) = C(1) / (1 - C(2))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(2) - C(1)/(1 - C(2))	0.904655	0.114260

Delta method computed using analytic derivatives.

TRANSINF

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	10.476081	276	0.0000
F-statistic	80.000491	(1, 276)	0.0000
Chi-square	80.000491	1	0.0000

Null Hypothesis: C(3) = C(1) / (1 - C(3))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(3) - C(1)/(1 - C(3))	0.232084	0.022154

Delta method computed using analytic derivatives.

ICTINF

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	7.877201	276	0.0000
F-statistic	62.05030	(1, 276)	0.0000
Chi-square	62.05030	1	0.0000

Null Hypothesis: C(4) = C(1) / (1 - C(4))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(4) - C(1)/(1 - C(4))	0.904368	0.114808

Delta method computed using analytic derivatives.

WATERINF

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	7.064884	276	0.0000
F-statistic	49.91258	(1, 276)	0.0000
Chi-square	49.91258	1	0.0000

Null Hypothesis: C(5) = C(1) / (1 - C(5))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(5) - C(1)/(1 - C(5))	0.905772	0.128208

Delta method computed using analytic derivatives.

AGRICINF

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	7.719651	276	0.0000
F-statistic	59.59301	(1, 276)	0.0000
Chi-square	59.59301	1	0.0000

Null Hypothesis: C(6) = C(1) / (1 - C(6))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(6) - C(1)/(1 - C(6))	0.902543	0.116915

Delta method computed using analytic derivatives.

CU

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	7.877310	276	0.0000
F-statistic	62.05202	(1, 276)	0.0000
Chi-square	62.05202	1	0.0000

Null Hypothesis: C(7) = C(1) / (1 - C(7))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(7) - C(1)/(1 - C(7))	0.904369	0.114807

Delta method computed using analytic derivatives.

FDI

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	7.856362	276	0.0000
F-statistic	61.72242	(1, 276)	0.0000
Chi-square	61.72242	1	0.0000

Null Hypothesis: C(8) = C(1) / (1 - C(8))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(8) - C(1)/(1 - C(8))	0.904301	0.115104

Delta method computed using analytic derivatives.

FSD

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
t-statistic	7.657790	276	0.0000
F-statistic	58.64175	(1, 276)	0.0000
Chi-square	58.64175	1	0.0000

Null Hypothesis: C(9) = C(1) / (1 - C(9))
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(9) - C(1)/(1 - C(9))	0.902884	0.117904

Delta method computed using analytic derivatives.

APPENDIX 1 – DESCRIPTIVE STATISTICS

	REALSP	AGRIC	MANUF	AGRICEMP	MANUEMP	ELECTINF	TRANSINF	ICTINF	WATERINF	AGRICINF	CU	FDI	FSD
Mean	38.24584	29.27082	8.975022	49.29491	15.33983	36.66574	2.220671	204.2548	4.872121	45.48537	3.12E+09	4.659888	15.91325
Median	37.01450	26.45647	8.680379	47.30500	12.02500	33.56191	2.264531	49.27120	4.666091	46.07074	7.10E+08	2.432675	12.96014
Maximum	80.91544	79.04236	21.49191	89.57000	67.60000	95.81540	2.890000	49965.00	16.27645	76.25421	6.44E+10	103.3374	73.90753
Minimum	11.27042	4.632906	1.532609	10.56000	5.420000	1.200000	1.400000	0.000000	0.236957	14.63206	16871300	-2.544539	0.000000
Std. Dev.	11.87296	13.46874	4.360915	16.53487	13.19549	22.40961	0.258557	2747.895	3.802085	17.30017	8.74E+09	10.08475	12.94192
Skewness	0.551107	0.953409	0.369893	-0.119254	2.755596	0.491900	-0.281285	18.07667	0.557336	-0.043278	4.560362	7.057377	2.205579
Kurtosis	4.295891	4.190858	2.741119	2.305595	10.01942	2.400330	3.102540	327.8455	2.526944	1.857982	24.92513	59.11301	8.670692
Jarque-Bera	39.79536	69.49382	8.446662	7.412417	1095.126	18.25266	4.496246	1468935.	20.16126	18.03582	7753.610	46033.57	709.7071
Probability	0.000000	0.000000	0.014650	0.024571	0.000000	0.000109	0.105597	0.000000	0.000042	0.000121	0.000000	0.000000	0.000000
Sum	12621.13	9659.369	2961.757	16267.32	5062.144	12099.69	732.8214	67404.07	1607.800	15010.17	1.03E+12	1537.763	5251.371
Sum Sq. Dev.	46378.23	59682.93	6256.782	89949.20	57285.77	165220.7	21.99420	2.48E+09	4755.975	98468.34	2.52E+22	33459.99	55105.33
Observations	330	330	330	330	330	330	330	330	330	330	330	330	330