ADDIS ABABA UNIVERSITY SCHOOL OF GRADUATE STUDIES

THE RELATIONSHIP BETWEEN UNEMPLOYMENT AND ECONOMIC GROWTH IN SUB–SAHARA AFRICAN COUNTRIES:A PANEL VECTOR AUTOREGRESSION APPROACH

BY:

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This is to certify that the paper prepared by Muhammed Osman, entitled: "THE RELATIONSHIP BETWEEN UNEMPLOYMENT AND ECONOMIC GROWTH IN SUB–SAHARA AFRICAN COUNTRIES: A PANEL VECTOR AUTOREGRESSION APPROACH" and submitted in Partial Fulfillment of the Requirements for the degree of masters of arts in Applied Economic Modeling and Forecasting (Fiscal Policy Analysis and Management) complies with the regulations of the university and meets the accepted standards with respect to originality and quality.

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List of Acronyms

ADF	Agmented Dickey Fuller
ARDL	Autoegressive Distributed Lag
CADF	Cross sectionaly Agmented Dickey Fuller
DOLS	Daynamic Ordinary Least Squars
FDI	Forein Direct Investment
FM	Fully Modified
FMOLS	Fully Modified Ordinary Least Squars
GDP	Gross Domestic Product
G	Population Growth
IRF	Impulse Response function
OLS	Ordinary Least Squars
OECD	Organisation for Economic Co-operation and Development
PMG	Pooled Mean Group
PVAR	Panel Vector Auto Regression
SURE	Seemingly Unrelated Regression Equation
SSA	Sub-Sahara Africa
U	Unemployment

Abstract

This study examines the relationship between unemployment and economic growth using panel data for a panel of Sub-Sahara African countries for the period 1991-2014. The PMG regression technique result indicates that negative long run relationship between unemployment and economic growth. Both FDI and population growth stimulate economic growth in the region. However, the short-run association between economic growth and these variables are weak. Results from DOLS and FMOLS estimates indicate that there is negative relationship between unemployment and economic growth in the long run. The variance decomposition result shows that the effect of economic growth to reduce unemployment is minimal. Based on these findings, the study recommends that the policy makers of these countries must recognize the effect of economic growth in reducing unemployment and also using the growing population as an input for the economic growth of the region by designing appropriate education system.

CHAPTER ONE

1. Introduction

1.1. Back ground of the study

Unemployment is the macroeconomic problem that affects people most directly and harshly. The loss of a job means a reduced in the living standard and psychological distress for most of the people. Unemployment is a frequent topic of political debate and that most of the politicians often claim that their proposed policies would help to reduce it by creating jobs (Mankiw, 2009). Unemployment is an important macroeconomic variable & it is the issue of the world's developed as well as developing economies. High unemployment means that labor resources are not being used efficiently. Hence, full employment should be a major macroeconomic goal of any government because it maximizes output. According Robert J. Barro and Xavier Sala-i-Martin (1992), the recent theories of growth tends to endogenous growth theories, including the roles of increasing returns, research and development Activity, human capital, and the diffusion of technology.

There is a widely accepted view in economics that the growth rate of the GDP of an economy increases employment and reduces unemployment. This theoretical proposition relating to output and unemployment is generally known as "Okun's Law". According to the Economic Commission for Africa 2011 Policy brief, Even though Africa experiences a relatively high growth rates in the first decade of the 21st century the growth episode was not accompanied by meaningful growth in employment. Unemployment rates were estimated to have risen from 7.4 per cent to 8.2 per cent between 1998 and 2009 in Sub-Saharan Africa (SSA) and from 12.8 per cent to over 13 per cent in North Africa over the same period. As a result of high unemployment and the fact that even those are employed struggle to find decent work in the formal sector, poverty rates remained chronically high in Africa over the last three decades.

1.2 Statement of the problem

Unemployment is a multi-dimensional occurrence such as an economical occurrence, it shows imbalance in economic activities and a social occurrence because of its effects on the social structure of the society, which is it affects the social cohesion. Even though those countries with slow economic growth and high population growth affected more, the phenomenon of unemployment is a global occurrence that affects both advanced as well as developing countries. The most important priority of the economic policies tends to increase the economic growth. Economic growth is a continuous and integrated process of interaction with interrelations working to increase the production capacity of the national economy in the long run; to raise real national income as well as the level of real per capita income (Nicholas, 1991). Economic policies that are directed to reduce unemployment rates emanate from approaches assuming that unemployment is directly linked with the economic growth. However, the theoretical and empirical research on the relationship between economic growth & unemployment rate indicates that both the evolution of opinions and the lack of agreement in providing explanation for the subject matter. According to Katarzyna Nagel (2015), the basic relationship between economic growth & unemployment rates are:

a. The creation effect (a negative correlation between growth and unemployment),
b. the creative destruction effect (a positive correlation between growth and unemployment);
c. the pool of saving effect (a negative correlation between growth and unemployment) ,and

d. The coordination failure effect (a negative correlation between growth and unemployment), were identified. Moreover, new relationships, triggered by institutional factors, were discussed: the minimum wage effect or the legal employment protection.

In this paper, GDP per capita growth, Unemployment, Population growth, foreign direct investment (net inflows) variables are used.

1.3 Objective of the study

The overall objective of this study is to determine the relationship between unemployment and economic growths in Sub-Sahara African countries.

The Specific objectives are:

- ✓ To show trends of economic growth and Unemployment in Sub-Sahara African countries;
- ✓ To determine the relationship between unemployment and economic growth both in the short and long run SSA countries;
- ✓ To give recommendation for policy makers on the subject matter.

1.4 Significance of the study

Unemployment is regarded as a “forgone output”. This is because, it divests the resource; which needed to build the economy (i.e., means the government losses its tax revenue & it incurs costs for the unemployed). When there is long run unemployment, the unemployed professionals will lose their knowledge & skills on their specialty. The professionals will be under employed in the formal sector or employed in the informal sector this leads to increase in the number of unskilled labours in the economy. If these options not hold the unemployed may migrate from one place to other place inside the country or out of the country. In Sub-Sahara African countries, there is high rural urban migration and high level of human trafficking in this region. Therefore, it is important to know the relationship between unemployment & economic growth to design appropriate policies to reduce the unemployment level and create a suitable economic environment to absorb the increasing labor force in the economy thereby foster economic growth. The paper will help the policy makers to design appropriate policies to reduce the unemployment in the region and to increase economic growth. Furthermore, it will be used as reference for further investigation by other researchers on the topic.

1.4 Scope and limitations of the study

1.4.1 Scope of the study

The study covered 34 Sub-Sahara African countries for periods ranging from 1991 to 2014.

1.4.2 Limitation of the study

The researcher encountered some issues related to variables which should be included in the study such as government expenditure, human and physical capital and so on. The researcher is unable to find data for the variables included in the study for the sample period before 1991. Even for the variables used for the study there is no data for some Sub-Sahara African countries because of that the number of the countries used in the sample is reduced to 34.

1.6 Organization of the study

Chapter two discusses both theoretical and empirical literatures in Sub-Saharan African countries. Chapter three devotes to the analysis of the study. Chapter four discusses the results of this paper. The last chapter explains the conclusion and recommendation of this paper.

CHAPTER TWO

2. Literature Review

2.1. Theoretical Review:

2.1.1. Unemployment

Definition and concepts

According to the Resolution concerning statistics of work, employment and labour underutilization adopted in 2013 by the 19th International Conference of Labour Statisticians, the standard definition of unemployment refers to "all those persons of working age who are without work, seeking work (carried out activities to seek employment during a recent period comprising the last four weeks or one month), and currently available for work". Furthermore, future starters of work are regarded as unemployed. The long-term unemployment can be defined as those people with duration of search for employment a period of lasting 12 months or more, including the reference period.

It is the macroeconomic problem that has a direct and severe impact on the life of the people. For most of the people, loss of job means a reduction on the living standard which results psychological distress. It is a frequent topic of political debate and those politicians often to gate the vote of the people claim that their proposed policies would help for the creation of more jobs. Economists study unemployment to identify its cause and to help for the improvement of the public policies that affect the unemployed. Some of the policies to affect the unemployed suggested by economists such as "job-training programs, unemployment insurance and Laws mandating a high minimum wage" used for the unskilled and skilled members of the labor force (Mankiw, 2009).

Based on the period of time it takes, unemployment can be divided in to two. These are short run and long run unemployment. Short-term unemployment by its nature "frictional and it is unavoidable". Unemployed workers in the short run may need some time to search for the job best suited to their skills and tastes. On the other hand, long-term unemployment is more likely to be "structural, representing a mismatch between the number of jobs available and the number of people who want to work" (Mankiw, 2009).

According to the United States Congressional budget office study (2012), factors causing the raise of long term unemployment are:

- ✓ *Weak demand for goods and services, as a consequence of the recession and its aftermath, which results in weak demand for workers;*
- ✓ *Mismatches between the needs of the employers and the skills or location of the unemployed;*
- ✓ *Incentives from extensions of unemployment insurance for people to stay in the labor force and continue searching for work; and*
- ✓ *The erosion of unemployed workers' skills and the belief held by some employers that people who have been unemployed for a long time would be low quality workers.*

Nichols, Mitchell, and Lindner (2013) explained the consequences of long run unemployment such as "declining income and consumption, declining reemployment wages, declining human and social capital, impacts on future labor market attachment, impacts on physical and mental health, impacts on children and families and impact on communities".

Theory of Unemployment

Keynesian and Classical Unemployment

Both the Keynesian and classical economists started from a common framework of model. They assumes that, a single composite good, output, produced under conditions of diminishing returns to each scarce factor of production and constant returns to scale production function. The conditions of production are controlled by the production function, and the demand for labor is derived from this function. The supply of labor is based on individual's decision to give up other activities and allocate time to labor. These relations yield a negatively sloped aggregate demand curve for labor relating offers of employment and the relative price of labor, or real wage, and a positively sloped supply curve of labor. The intersection of the two curves determines the market clearing real wage and the equilibrium level of employment. Therefore, according to the Keynesian and the classical scholars, unemployment is defined as the difference between the amount of employment demanded and supplied at each real wage or as the difference between actual and equilibrium employment (Brunner and Meltzer, 1978).

As cited in Hornstein etal.(2005), the relationship between unemployment and the rate of technological change has two approaches. The first approach is Aghion and Howitt (1998) in which they argued that new equipment enters the economy through the creation of new matches (i.e, the "creative destruction effect"). The other approach is Mortensen and Pissarides (1998) proposed that the new technologies enter into firms through the process of upgrading plant units (Hornstein, Krusell and Violante, 2003).

Unemployment in Sub-Saharan Africa

According to the Economic Commission of Africa 2011 Policy brief, Even though Africa experiences a relatively high growth rates in the first decade of the 21^{st} century the growth episode was not accompanied by meaningful growth in employment. Unemployment rates were estimated to have risen from 7.4 per cent to 8.2 per cent between 1998 and 2009 in Sub-Saharan Africa (SSA) and from 12.8 per cent to over 13 per cent in North Africa over the same period. As a result of high unemployment and the fact that even those are employed struggle to find decent work in the formal sector, poverty rates remained chronically high in Africa over the last three decades.

2.2.1. Economic Growth

Definition and concepts

Economic growth is defined in many ways. According to Todaro and Smith (2003) economic growth defined as a steady process by which the productive capacity of the country's economy is increased over a period of time to bring about rising levels of national output and income. Gillis *et al.* (1987) also defined Economic growth as a rise in per-capita income and product, where income per-capita is measured as the gross national product divided by the total population. However, Kuznets (1974) proposes a broad definition of economic growth and it should not be narrowly confined to changes in the level of output or income, rather it should include major structural changes and correspondingly large modifications in social and institutional conditions under which the increase in output or income is attained. He defined a country's economic growth as a long-term rise in capacity to supply varied types of goods and services to its population, and this growing in capacity is based on advancing the technology and the Economic growth implies the increase in per-capita real gross domestic product (GDP), this means widening of the scale of production in a country as a whole, or more efficient use of its scarce economic resources to produce goods and services. Therefore, the scale of production or productivity can only be increased in the long run; secular economic growth is considered a long run phenomenon.

There are two types of growth were the extensive and intensive growth. According to Reynolds (1985) defines extensive growth as a situation where an increase in GDP is fully absorbed by population increase with no upward trend in per capita income. In the other hand intensive growth is where GDP growth exceeds population growth, allowing a sustained rise in living standards as measured by real income per capita (Brian and Howard, 2005).

The aim of every nation in the world is economic growth and development. But the basic issue here is that what are the sources of growth? The answer for this question is that the sources of growth can be proximate or fundamental cause. The first one is proximate causes relate to the accumulation of factor inputs in the form of capital and labour, and also variables which influence the productivity of these inputs, such as scale economies and technological change. The research of growth accountants such as Denison (1967, 1974, 1985), Jorgensen (1996, 2001) and Maddison (1972, 1987, 1995) has produced a useful taxonomy of the various proximate sources of growth, and the neo-Keynesian, neoclassical and endogenous growth theories tend to concentrate on modeling of these proximate variables. Most of the influential growth theories such as the neo-Keynesian Harrod–Domar model, the Solow–Swan neoclassical model and the

Romer–Lucas-inspired endogenous growth models based on proximate causes (as cited in Brian and Howard R 2005).

Second the fundamental or deep sources of growth relate to those variables that have an important influence on a country's ability and capacity to accumulate factors of production and invest in the production of knowledge. According to Temple (1999) population growth, the influence of the financial sector, the general macroeconomic environment, trade regimes, the size of government, income distribution and the political and social environment considered. In addition the 'deeper' determinants of growth include the importance of institutions and incentive structures (North, 1990; Olson, 2000), trade and openness (Krueger, 1997; Dollar and Kraay, 2003) and the impact of geography (Bloom and Sachs, 1998) (as cited in Brian and Howard R 2005).

A Brief History of Growth Theories

Many literatures suggest that Adam Smith's (1776) *An Inquiry into the Nature and Causes of the Wealth of Nations* may be seen as a suitable starting point for economic growth theories. According to Smith (1776) capital accumulation, technological progress and institutional and social factors play an important role in the economic development process of a country (Kibritcioglu, 1997). Based on the Smith (1776) idea of long-run steady state economists other economists starting from David Ricardo to Roy Harrod, Harrod's (1939) and Domar's (1946) Keynesian growth models concede that factors of production are not substitutable and investment decisions are functions of expected demand for goods and service. In the standard Keynesian growth model there is unstable balanced growth path if the economy is closed due to a fixed-coefficient production function and the existence of an independent investment function given investor expectations regarding future demand for goods and services. As a result of the model, government policies can affect the long-run growth rate of real output in the economy.

The succeeding Neo-classical economists such as Ramsey (1928), Solow (1956), Swan (1956), Cass (1965), and Koopmans (1965) develop another growth model. The basic assumptions of their growth model are constant returns-to-scale, diminishing marginal productivity of capital, exogenous production technology, substitutability of capital and labor, and lack of an independent investment function. However, the neoclassical growth model suggests that the steady state growth rate, aside from exogenous technological progress, is zero. This implies that conventional macroeconomic policies such as government investment can affect the level of per-capita income but they have no effect on the long run growth rate of the economy. Continues exogenous technological improvements can compensate for the negative effect of decreasing marginal productivity of capital thereby leading to long run growth**.** Finally, in many neoclassical growth models exogenously determined constant population growth rate is the main determinant of percapita real income level.

The neoclassical growth model also tries to tell about how developed and less developed economies growth converges in the long run. Regarding to this idea, there are two theories that is the absolute and conditional convergence. The idea of the absolute convergence is that countries with the same steady state capital per-worker but different initial relative factor endowments and per-capita incomes will grow at different rates to eventually reach the same per-capita income level. This theory assumes that poor countries fast-growing and rich countries slow-growing is based on the assumption that technology, the saving rate, and population growth rate are all identical across countries, and that returns to capital are diminishing. This hypothesis was to become a major point of disagreement with the subsequent endogenous-growth theory economists, in particular following Romer (1986) and Lucas (1988). The idea of conditional convergence is that countries with different parameters and different steady-state capital per-worker targets will grow at different rates but those with similar parameters will converge to reach the same per-capita output level. This theory is accepted by many economists such as Barro (1991), Mankiw et al. (1992) and Barro and Sala-i- Martin (1992) and there are many evidences in favor of this.

P. Romer, R. Lucas and other proponents of endogenous growth theory argued that, unlike physical capital, human capital may be augmented by non-diminishing returns, which permits economic growth to continue indefinitely. Accordingly, technological progress occurs as a purposeful economic activity when profit maximizing agents seek out newer and better products. Inventions are rewarded with an ex-post monopoly power through patents to cover the high cost of initial investments necessary to bring new products to the market. There is another dimension of the economics of new ideas or technology: innovations have a public component (externality) in that they raise the productivity of all subsequent innovators (knowledge spillover effect). Ultimately the growth rate of an economy depends on Research & Development technology, the degree of firms' monopoly power (apropriability of new technologies) and time horizon of investors.

Endogenous growth models developed within the framework of inter-temporal optimizing behavior of rational agents represent different intellectual influences. Some models can be broadly considered as an extension of the Schumpeterian or the institutional tradition. Some others have strong neo-Smithian or still a neoclassical background. Some of these models are even called Harrod-type growth models.

The first generation endogenous growth models achieve positive and constant steady state growth rates both by assuming non-decreasing returns-to-scale and by endogenizing technological improvements; e. g. Romer (1986, 1990), Lucas (1988) and Becker et al. (1990). That is, technological spillover effects resulting from investments in research & development, human capital or technological infrastructure ensure a self-feeding growth process in the economy. Another class of models known as the "AK type" replaces the assumption of diminishing marginal productivity of capital with the *non*-diminishing marginal productivity of the accumulable factor of production to achieve positive and sustainable steady state growth rate in the economy; e. g. Jones and Manueli (1990) and Rebelo (1991).

Endogenous growth models, no matter whether they are "scale" or "AK-type" models emphasize the important role of governments' fiscal, technology, and education and health policies in the process of economic development. They also leave some room to historical, cultural and sociological factors as determinants of long-run growth.

However, empirical evidence does not strongly support either the absolute convergence idea of some neoclassical models or the existence of increasing returns-to scale in endogenous growth models. The idea of the increasing returns to scale in the production led to the development of non-scale growth model, which is much closer to the neoclassical model. Jones (1995), for example, argues that the steady state growth rate is independent of traditional macroeconomic policies. However, because of slow convergence speeds in the transition process, these policies can lead to remarkable long run effects on the *level* of per-capita income.

While the augmented Solow model better explains international differences in living standards, it cannot account for the persistence of economic growth. Endogenous growth theory attempts to show how persistent growth may take place without having to resort to exogenous technological progress (Bernanke and Gurkaynak, 2001).

Economic growth in Sub-Saharan Africa

Even though there were some success stories in the economy of Africa in the 1960's and early 1970's, Africa is poor and getting poorer. There is also an almost universally pessimistic consensus about its economic prospects. This emerged at the start of the recent empirical work on the determinants of growth with Barro's (1991) discovery of a negative "African Dummy" and was summed up by Easterly and Levine's (1997) title, "Africa's Growth Tragedy." Further detailed research into African economic performance during that period confirms it is a story not of persistent failure, but rather of periods of growth, followed by reversals which often erase any gains that were made during the growth spurt (Jerven 2010). Since 1950 most African countries have followed a general pattern of growth and reversal. Two decades of relatively rapid growth from 1950 ended with the oil crisis of the 1970s, and were followed by stagnation or negative growth in the 1980s and 1990s. In most countries, the recent revival of growth began in the late

1990s, offsetting some of the decline of the previous two decades (as cited in Ndulu and O'Connell, 2008).

Yet these things now a time is changed there are many prospect the growth of sub- Saharan e.g., the African economic report in 2015 shows that the GDP growth in Sub-Saharan Africa averaged 4.5 percent in 2014, it is increased from 4.2 percent in 2013.

Unemployment and economic growth

Unemployment is highly reliant on economic activity, that is when economic activity is high, more production will happens as overall, and more workers are needed to produce the higher amount of products. And when economic activity is low, firms reduce their workforce as a result unemployment rises. From this we can understand that unemployment is *countercyclical*, that is it rises when economic growth is low and decline when economic activity is rise (IMF ,2012).

The relationship between economic growth and the unemployment rate may be a loose one in the short run. That is, unemployment does not fall in lockstep with an increase in growth. The reasons that unemployment may not fall appreciably when economic growth first picks up after a recession's end is that some firms may have underutilized employees on their payrolls by reducing work hours or by imposing some pay cuts because laying off workers when product demand declines and rehiring them when product demand improves has costs. As a result, employers may initially be able to increase output to meet rising demand at the outset of a recovery without hiring additional workers by raising the productivity of their current employees. This temporarily boosts labor productivity growth above its trend rate. Once the labor on hand is fully utilized, output can grow no faster than the rate of productivity growth until firms begin adding workers. Unemployment starts rising only when the downturn is prolonged. The unemployment follows economic growth with a delay; it is considered as a *lagging indicator* of economic activity.

As an economic expansion progresses, output growth will be determined by the combined rates of growth in the labor supply and labor productivity. As long as growth in real gross domestic product (GDP) exceeds growth in labor productivity, employment will rise. In other words employment growth is more rapid than labor force growth, the unemployment rate will fall.

This negative relationship between change in the rates of real GDP growth and unemployment termed as “Okun’s law”. This named after the early 1960s U.S. economist Arthur Okun, who postulates that a decline in unemployment by 1 percentage point corresponds to a 3 percent rise in output based on the US economy. More recent estimates find that the consequent rise in output may be lower, possibly between 2 and 3 percent.

The key thing to the long-run relationship between changes in the rates of GDP growth and unemployment is the rate of growth in potential output. Potential output is an unobservable measure of the capacity of the economy to produce goods and services when available resources, such as labor and capital, are fully utilized. The rate of growth of potential output is a function of the rate of growth in potential productivity and the labor supply when the economy is at full employment.

If the unemployment rate is high then actual GDP falls short of potential GDP. This is referred to as the output gap. In the absence of productivity growth, as long as each new addition to the labor force is employed, growth in output will equal growth in the labor supply.

If the rate of GDP growth falls below the rate of labor force growth, there will not be enough new jobs created to accommodate all new job seekers. As a result, the proportion of the labor force that is employed will fall. Put differently, the unemployment rate will rise. If the rate of output growth exceeds the rate of labor force growth, some of the new jobs created by employers to satisfy the rising demand for their goods and services will be filled by drawing from the pool of unemployed workers this leads to the unemployment rate will fall.

If GDP growth equals labor force growth in the presence of productivity growth, more people will be entering the labor force than are needed to produce a given amount of goods and services. The share of the labor force that is employed will fall. Expressed differently, the unemployment rate will rise. Only as long as GDP growth exceeds the combined growth rates of the labor force and productivity (potential output) will the unemployment rate fall in the long run. Knowing what that rate of GDP growth is might be useful to policymakers interested in undertaking stimulus policies to bring down the unemployment rate. But as just stated, the rate of output growth necessary to lower the unemployment rate requires knowledge of the rates of labor force and productivity growth. Both have changed over time (Levine L., 2013).

2.2 Empirical literature review

The macroeconomics issue of how unemployment is related to economic growth was dealt by many economists in advanced economies by economists such as Bean and Pissaride (1993), Aghion and Howitt (1994) and Daveri and Tabellini (2000).Some economists such as Bean and Pissaride (1993) deals with the long-run effects of economic growth on unemployment for OECD countries proves and the result shows there is significant relationship between growth and Unemployment.

Yerdelen F., 2011 examine the relationships between unemployment rate and economic growth in European Countries over the period 1977-2008. The result shows that there is long term relationship between GDP and unemployment rate, but the long run coefficients obtained from the study are lower compared to the coefficient obtained by Okun. The short run relationship is different in different countries.

There are many studies dealt with the relationship between unemployment and economic growth in developing countries. This paper tries to mention few of them. Accordingly, David Castells-Quintana and Vicente Royuela on June 2012, investigates the effects of unemployment and income inequality on economic growth in 48 countries with different levels of economic development over the period from 1990 to 2007 using reduced form model and they suggested that while initial high unemployment rates do not seem to be significant for subsequent long-run growth, they do have a significantly negative effect when interacting with increases in income inequality.

Al-Habees & Abu Rumman (2012) studied the relationship between economic growth and unemployment in the Jordanian economy and some Arab countries. They have found that there is a very positive trend for the high growth rates and the relative decline in the unemployment rate, but that does not confirm the existence of a strong relationship between growth and unemployment.

There are many literatures done using the panel VAR models for this work the researcher mentions few of it. Such as Seetanah, B.,*etal* 2010 employed rigorous panel VAR procedures to examine the complex linkages between stock market development, bank development and economic growth for the case of 27 developing countries over a period of 1991-2007. Even though there is relative lower magnitude as compared to banking development, Results from the analysis showed that stock market development is an important ingredient of growth. Stock market development and banking development are seen to be complement to each other and moreover there are important indirect effects through 'investment channel' to growth.

Salahuddin Mohammad and Gow Jeff (2015) studies the effect of the Internet on economic growth in 11 Southern African countries using a combination of panel and time series approaches .The variables used are Internet usage, economic growth, financial development and trade openness using panel data for the period 1990-2012. The Pooled Mean Group regression technique result indicates a positive long run relationship between Internet usage and economic growth at 1% level of significance. Both financial development and trade openness stimulate economic growth in the region. However, the short-run association between economic growth and these variables are insignificant. The results from Dynamic Ordinary Least Squares (DOLS) and Fully Modified Ordinary Least Squares (FMOLS) methods support the panel results for most of the countries. From the above review we can infer that there is a relationship between unemployment and economic growth.

CHAPTER THREE

3. Data and Methodological framework

3.1 Data

This study used a panel dataset for 34 Sub-Sahara African countries for the period 1991- 2014. The core variables used in the study will GDP per capita growth, Unemployment, Population growth and foreign direct investment -net inflows for this work.

Data for all these variables were obtained from the World Data Bank, 2015 (previously, World Development Indicators (WDI) database).

3.2 Methodology

3.2.1. The model

A panel Vector Auto Regression (PVAR) used for analysis this work. Panel-data vector auto regression combines the traditional VAR approach, which treats all the variables in the system as endogenous, with the panel-data approach, which allows for unobserved individual heterogeneity. An econometric model with per capita GDP growth rate as a function of Unemployment, Population growth rate and foreign direct investment -net inflows as economic growth model will develop. Therefore, the growth equation used in the study will:

$$GDP_{it} = \beta_0 + \beta_1 U_{it} + \beta_2 g_{it} + \beta_3 FDI_{it} + \varepsilon_{\text{it}} \ldots \ldots \ldots \ldots \ldots (1)$$

Where $\varepsilon_{\text{it}} = \mu_{it} + v_{it}$ while $\mu_{it} \approx (0, \delta^2 \mu)$ and $v_{it} \approx (0, \delta^2 v)$ are independent of each other and among themselves. μ_{it} denotes country specific fixed effect and v_{it} denotes time variant effect. The subscript i represents country (i= 1....34) and t represents time period from 1991 to 2014.

GDP_{it}= Per capita GDP growth rate

U_{it}=Unemployment rate

g_{it}=Population growth rate

FDI_{it}= Foreign direct investment -net inflows

The researcher specifies a first order PVAR model as follows:

$$Z_{it} = \Gamma_{0i}(t) + \Gamma_i(\ell)Z_{it-1} + \varepsilon_{it} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.. (2)$$

Where Z_t is a four - variable vector (GDP, FDI, g, U) and the variables are as defined previously "i" to index countries and "t" to index time, Γ's are the parameters and ε_t is the error term.

PVAR is a very important tool in analyzing policy issues. According to Canova, F. and Ciccarelli, M. (2013) PVARs are suited to addressing issues that are frequently under discussions in academics and in the policy arena because they are able: to capture both static and dynamic interdependencies, to treat the links across units in an unrestricted fashion, to easily incorporate time variation in the coefficients and in the variance of the shocks, and to account for cross sectional dynamic heterogeneities.

Even though the PVAR models are powerful in policy analysis, they are not free from challenges both in terms of estimation and inference. According to Koop and Korobilis (2012) VARs model have fast system to estimate large scale time varying coefficients but it is not clear whether these will work or not in time varying coefficients of PVAR, where cross sectional shrinkage becomes important. In addition, according to Sims and Zha (2006) it is not clear how to expand the Markov switching methods to a panel data framework and whether transition probabilities should features important cross unit heterogeneities. The properties of estimators used have not been evaluated in relevant economic situations and it is unclear whether tests for model selection or for validation exercises are powerful or not. For the identification, except for De Graeve and Karas (2012), all the techniques are traditional ones used in VARs , no effort has been made to exploit the richness of the cross sectional information and no effort has been made to directly link panel VARs to the DSGE modes (as cited in Canova, F. and Ciccarelli, M. 2013).

3.2.2 Estimation procedures

There are a number of references related to PVAR estimation among these Gutierrez, L. (2003), Pesaran H.*etal* (1999), (1995) and (1996) and Pesaran, M. H. (2007) and (2004) and many others.

The researcher performs the following estimation techniques for the study:

3.2.2.1 Unit root tests to verify the stationarity of data.

Testing for unit roots in time series studies is a common practice among applied researches and has become an integral part of econometric courses. However, testing for unit roots in panels is a resent phenomenon. The development of panel unit roots classified in to two generations: the first generation and the second generation. The first generation has also two parts the homogenous and the heterogeneous parts. In the homogenous part there are different tests, Breitung (2000), Hadri (2000) and Levin, Lin, and Chu (2002).In the hegrogeneous part also there are different tests such as Maddala and Wu (1999),Choi (2001) and Im, Pesaran and Shin (2003). The Second generation of panel unit root tests are O'Connell (1998), Breitung and Das(2005), Moon and Perron (2004), Bai and Ng (2004) and Pesaran (2003).

First Generation Unit root Tests

Levin, Lin, and Chu (2002)

According to Levin, Lin, and Chu individual unit root tests have limited power against alternative hypothesizes with highly persistent deviations from equilibrium. This issue is particularly severe in small samples. Therefore Levin, Lin, and Chu suggest that a more powerful panel unit root test than performing individual unit root tests for each cross-section in the panel. The null hypothesis for this test is that each individual time series contains a unit root against the alternative that each time series is stationary.

The hypothesis Levin, Lin, and Chu used is that

$$\Delta y_{it} = \rho y_{it-1} + \sum_{L=1}^{pi} \theta_{iL}\, \Delta y_{it-L} + \alpha_{mi} d_{mt} + \varepsilon_{it} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (3) \qquad m = 1,2,3$$

With d_{mt} indicating the vector of deterministic variables and α_{mi} the corresponding vector of coefficients for model m =1,2,3 . In particular, $\mathrm{d}_{1\mathrm{t}} = \emptyset\{\text{empty set}\}$, $d_{2t} = \{1\}$ and $d_{3t} = \{1, \mathrm{t}\}$.

Since the log order p_i is unknown, Levin, Lin, and Chu suggest a three-step procedure to implement their test.

Step 1: Perform augmented Dickey-Fuller (ADF) regressions regressions and generate orthogalized residuals

Step 2: Estimate the ratio of long-run to short-run standard deviations

Step 3: Compute the panel test statistics

Breitung (2000)

The Levin, Lin, and Chu and Im, Pesaran and Shin panel unit root tests require $n \to \infty$ such that $\frac{n}{T} \to 0$ .This implies that n should be small enough relative to T. From this we can understand that both Levin, Lin, and Chu and Im, Pesaran and Shin tests may not nominal size well when *n* is small relative to *T*. Breitung (2000) studies the local power of Levin, Lin, and Chu and Im, Pesaran and Shin test statistics against a sequence of local alternatives . The study result shows that the Levin, Lin, and Chu and Im, Pesaran and Shin tests suffer from a dramatic loss of power when individual-specific trends are included. This is because of the bias correction that leads to the removal of the mean under the sequence of local alternative.

Hence, Breitung suggests a test statistic that does not employ a bias adjustment whose power is substantially higher than that of Levin, Lin, and Chu or the Im, Pesaran and Shin tests based on the Monte Carlo experiments. So, the results indicate that the power of Levin, Lin, and Chu and Im, Pesaran and Shin tests is very sensitive to the specification of the deterministic terms.

Hadri (2000)

Hadri (2000) develops a residual-based Lagrange multiplier test. The null hypothesis for the test is that there is no unit root in any of the series in the panel against the alternative of a unit root in the panel.

Hadri (2000) considers the following two models:

$$y_{it} = r_{it} + \varepsilon_{it} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots .. (4) \qquad and$$

$$y_{it} = r_{it} + \beta_{it} + \varepsilon_{it} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots .. (5) \quad i = 1, \dots, n; t = 1, \dots, T$$

Where $r_{it} = r_{i,t-1} + u_{it}$ is a random walk. $\varepsilon_{it} \sim IIN(0, \delta_\varepsilon^2)$ and $u_{it} \sim IIN(0, \delta_u^2)$ are mutually independent normal that IID across "i" and over "t".

Using back substitution, model 2 becomes

$$y_{it} = r_{i0} + \beta_i t + \sum_{s=1}^{t} u_{is} + \varepsilon_{it} = r_{i0} + \beta_i t + v_{it} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots .. (6)$$

Where $v_{it} = \sum_{s=1}^{t} u_{is} + \varepsilon_{it}$. The stationary hypothesis is simply $H_0: \delta_u^2 = 0$, in which case $v_{it} = \varepsilon_{it}$.

Im, Pesaran and Shin Test (IPS 2003)

The Levin, Lin, and Chu test requires ρ to be homogeneous across "i". This implies that the Levin, Lin, and Chu test is restrictive. However, Im *et al*. (2003) extends the assumption of homogeneous and allow the incorporation of a heterogeneous coefficient of $y_{i,t-1}$. Hence, Im, Pesaran and Shin propose an alternative testing procedure based on averaging individual unit root test statistics. Im, Pesaran and Shin suggest an average of the ADF tests when u_{it} is serially correlated with different serial correlation properties across cross-sectional units. The null hypothesis for this test is that each series in the panel contains a unit root, i.e., $H_0: \rho_i = 0$ for all i against the alternative hypothesis allows for some (but not all) of the individual series to have unit roots, i.e,

$$H_1: \begin{cases} \rho_i < 0 \;\; for\ i = 1,2,\dots,n_1 \\ \rho_i = 0\ for\ i = n_1 + 1,\dots,n \end{cases}$$

This test requires a condition that the fraction of the individual time series that are stationary to be nonzero, i.e., $\lim_{n\to\infty}(n_1/n) = \delta$ where $0 < \delta \leq 1$. This condition is also necessary for the consistency of the panel unit root test.

Maddala and Wu (1999) and Choi (2001)

Similar to the Im, Pesaran and Shin test Maddala and Wu (1999) and Choi (2001) tests consider the heterogeneous nature of the data under investigation. Based on the assumption of heterogeneous they proposed a Fisher-type test as follows:

$$P = -2\sum_{i=1}^{n} \ln p_i \rightarrow \chi^2(2n) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (7)$$

which combines the p-values from unit root tests for each cross-section i to test for unit root in panel data.

In addition to the above Fisher-type test Choi (2001) proposes two other test statistics besides Fisher's inverse chi-square test statistic P. The first test statistics is the inverse normal test,which is

$$\mathrm{Z} = \frac{1}{\sqrt{\mathrm{n}}}\sum_{\mathrm{i}=1}^{\mathrm{n}} \phi^{\mathrm{i}}\,(\mathrm{p_i}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

where ϕ is the standard normal cumulative distribution function. Since$0 \leq p_i \leq 1$,

$\phi^{-1}(p_i)$ is a N (0,1) random variable and as $T_i \rightarrow \infty$ for all i, $Z \Rightarrow N$ (0,1).

The second test statistics is the logit test, which is

$$L = \sum_{\mathrm{i}=1}^{\mathrm{n}} \ln(\mathrm{p_i}|1 - \mathrm{p_i}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (9)$$

where $\ln(p_i|1 - p_i)$ has the logistic distribution with mean 0 and variance $\pi^2/3$. As $T_i \rightarrow \infty$ for all i, $\sqrt{mL} \Longrightarrow t_{5n+4}$ where $m = \frac{3(5n+4)}{\pi^2 n(5n+2)}$. When n is become large, Choi (2001) also proposed a modified P test, that is

$$p_m = \frac{1}{2\sqrt{n}}\sum_{i=1}^{n}(-2\ln p_i - 2) \Longrightarrow N(0,1)\ (T_i \rightarrow \infty followed\ by\ n \rightarrow \infty) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (10)$$

The distribution of the Z statistic is invariant to infinite n, and $Z \Longrightarrow N(0,1)$ as $T_i \rightarrow \infty$ and then $n \rightarrow \infty$.

Second generation panel unit root tests

The Seemingly Unrelated Regression Method

O'connell (1998) suggests estimating the unit root of the sytem by using a general least square estimator. Let $\hat{\Sigma} = \frac{1}{T}\sum_{i=1}^{T} \hat{\varepsilon}_t \, \hat{\varepsilon}_t'$ denote the sample covariance matrix of the residual vector. However, Breitung and Das (2005) suggested a bootstrap procedure that improves the size properties of the general least square test and also an alternative approach based on "panel corrected standard errors" is considered.

The methods of Common Factor

Cross-section dependence can arise due to a variety of factors, such as omitted observed common factors, spatial spillover effects, unobserved common factors, or general residual interdependence that could remain even when all the observed and unobserved common effects are taken into account.

Dynamic factor models have been used to capture cross-section correlation. Moon and Perron (2004c) consider the following model:

$$y_{it} = \alpha_i + \Lambda_i' f_t + y_{it}^{o} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (11)$$

$$y_{it}^{0} = \rho_i y_{i,t-1}^{0} + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (12)$$

where ε_{it} are unobservable error terms with a factor structure and $\alpha_i$are fixed effects.

ε_{it} is generated by M unobservable random factors f_t and idiosyncratic shocks e_{it} as follows:

$$\varepsilon_{it} = \Lambda_i' f_t + e_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (13)$$

where Λ_i are nonrandom factor loading coefficient vectors and the number of factors M is unknown. Each ε_{it} contains the common random factor f_t , generating the correlation among the cross-sectional units of ε_{it} and y_{it} . Moon and Perron treat the factors as nuisance parameters and suggest pooling defactored data to construct a unit root test. Let Q_Λ be the matrix projecting onto the space orthogonal to the factor loadings. The defactored data is YQ_{Λ} and the defactoreed residuals eQ_{Λ} no longer have cross-sectional dependence, where Y is a $T \times n$ matrix whose i-th column contains the observations for cross-sectional unit i.

Bai and Ng (2004) consider the above two modes and they test separately the stationarity of the factors and the idiosyncratic component. To do so, they obtain consistent estimates of the factors regardless of whether residuals are stationary or not. They accomplish this by estimating factors on first-differenced data and cumulating these estimated factors. Bai and Ng suggest pooling results from individual ADF tests on the estimated defactored data by combining p-values as in Maddala and Wu (1999) and Choi (2001). Pesaran (2003) suggests a simpler way of getting rid of cross-sectional dependence than estimating the factor loading. His method is based on augmenting the usual ADF regression with the lagged cross-sectional mean and its first difference to capture the cross-sectional dependence that arises through a single factor model. This is called the cross-sectionally augmented Dickey-Fuller (CADF) test. This simple CADF regression is

$$\Delta y_{it} = \alpha_i + \rho_i^* y_{i,t-1} + d_0 \bar{y}_{t-1} + d_1 \Delta \bar{y}_t + \varepsilon_{it} \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots .. (14)$$

where $\bar{y}_t$ is the average at time t of all n observations.

3.2.2.2 Panel co-integration test

Residual-Based Approaches to Panel Cointegration

Like the panel unit root tests, panel cointegration tests can be motivated by the search for more powerful tests than those obtained by applying individual time series cointegration tests. The latter tests are known to have low power, especially for short T and short span of the data.

Kao Tests

Kao (1999) presented two types of cointegration tests in panel data, the DF and ADF types tests. Consider the panel regression model

$$y_{it} = x'_{it}\beta + z'_{it}\gamma + e_{it} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. (15)$$

Where y_{it} and $x_{it}$are I (1) and noncointegrated. For $z_{it} = \{\mu\}$, Kao(1999) proposed DF and ADF-type unit root tests for e_{it} as a test for the null of no cointegration. The DF-type tests can be calculated from the fixed effects residuals

$$\hat{e}_{it} = \rho\hat{e}_{i,t-1} + v_{it} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.. (16)$$

Where $\hat{e}_{it} = \tilde{y}_{it} - \tilde{x}'_{it}\hat{\beta}$ and $\tilde{y}_{it} = y_{it} - \bar{y}_i$,$\tilde{x}_{it} = x_{it} - \bar{x}_i$. In order to test the null hypothesis of no cointegration, the null can be written as $H_0: \rho = 1$

The ADF type test also can be calculated using the following regression model:

$$\hat{e}_{it} = \rho\hat{e}_{i,t-1} + \sum_{j=1}^{p} \delta_j \, \Delta\hat{e}_{i,t-j} + v_{it} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. (17)$$

with the null hypothesis of no cointegration.

Pedroni Tests

Pedroni (1999, 2004) also proposed several tests of cointegration. This test assumes the null hypothesis of there is no cointegration in a panel data model by allowing considerable heterogeneity.

Pedroni considered the following type of regression:

$$y_{it} = \alpha_i + \delta_i t + X'_{it}\beta_i + e_{it} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (18)$$

for a time series panel of observables y_{it} and X_{it} for members i =1,…, N over time periods t =1,..,T , where X_{it} is an m-dimensional column vector for each member i and β_i is an m-dimensional column vector for each member i. The variables y_{it} and X_{it} are assumed to be I(1), for each member i of the panel, and under the null of no cointegration the residual e_{it} will also be I(1). The parameters α_i and δ_i allow for possibility of member specific fixed effects and deterministic trends, respectively. The slope coefficients β_i are also permitted to vary by individual, so that in general the cointegrating vectors may be heterogeneous across members of the panel.

The Dickey Fuller-type tests and ADF-type tests can be calculated from the fixed effects residuals

$$\hat{e}_{it} = \rho_i \hat{e}_{i,t-1} + v_{it} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (19)$$

$$\hat{e}_{it} = \rho_i \hat{e}_{i,t-1} + \sum_{j=1}^{p} \varphi_{ij}\, \Delta\hat{e}_{i,t-j} + v_{it} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (20)$$

The null hypotheses for cointegrated tests are:

$$H_0: \rho_i = 1;\ H_1: \rho_i = \rho < 1 \qquad\qquad (i = 1,2, \dots, N)$$

and

$$H_0: \rho_i = 1; H_1: \rho_i < 1 \qquad\qquad (i = 1,2, \dots, N)$$

Pedroni’s tests can be classified in to two categories. The first set (within dimension) is similar to the tests discussed above, and involves averaging test statistics for cointegration in the time series across cross-section. The second set (between dimension), the averaging is done in pieces so that the limiting distributions are based on limits of piecewise numerator and denominator terms. The basic approach in both cases is that first to estimate the hypothesized cointegration relationship separately for each member of the panel and then pool the resulting residuals when constructing the panel tests for the null of no cointegration. Specifically, in the first step, one can estimate the proposed cointegrating regression for each individual member of the panel in the form of the above model, including idiosyncratic intercepts or trends as the particular model warrants, to obtain the corresponding residuals $\hat{e}_{it}$. In the second step, the way in which the estimated residualsare pooled will differ among the various statistics.

3.2.2.3 Pooled Mean Group Regression estimation

Pooled mean group regression performed to estimate short - and the long-run relationship and the speed of error correction.

The conventional dynamic panel model with small T focuses only on allowing for intercept variation via individual effects. In comparison little attention has been paid to the implications of variation in slope parameters. There are three justifications for analyzing the dynamic heterogeneous panels.

First, the slope heterogeneity does not matter when the primary interest lies in obtaining an unbiased estimator of the average effect of exogenous variables.

Second, in the case where only relatively small time periods were available, the scope for analysing the slope heterogeneity explicitly appeared became limited. Considering now that panels with a reasonable time dimension are available and that the evidence of slope heterogeneity in panels is pervasive, it is a high time to examine the implications of slope heterogeneity directly.

A third possible justification is that the long-run responses which are often the primary focus of analysis are less likely to be subject to slope het-erogeneity than the short-run adjustment patterns across groups. Therefore, it is interesting to see how the time-series, cross-section and panel estimates of such long-run coefficients can be compared.

In practice the extent of cross-sectional heterogeneity may be so large as to preclude the use of pooling. An approach that is becoming increasingly popular in this context is to focus estimation and inference on so called mean group quantities that are averages î across panel units.

Consider the following dynamic heterogeneous panels,

$$y_{it} = \Phi_i y_{it-1} + x_{it}\beta_i + \varepsilon_{it} \dots\dots\dots\dots\dots\dots\dots (21) \qquad , i = 1, \dots, N, t = 1, \dots, T$$

Where assume that:

x_{it} and ε_{is} are uncorrelated each other for all t and s

$\Phi_i \sim iidN(\Phi, \omega_1^2)$.

$\beta_i \sim iidN(\beta, \Omega_2)$.

$\Phi_i and\ \beta_i\ are\ independently\ distributed\ with\ y_{1t}, x_{it}\ and\ \varepsilon_{it}\ for\ all\ t.$

The k- dimensional vectors x_{it} are covariance stationary processes.

Under the second and third assumptions this can be regarded as the standard random coefficients model. Under this scenario Pesaran and Smith (1995) have investigated the asymptotic as well as small sample properties of the following three alternative estimators:

1. The pooled (within) estimator, which involves pooling the data by imposing homogeneous slope coefficients, allowing for fixed or random effects.

2. The cross-section (between) estimator, which involves averaging the data over time per each group and estimating the cross-section regression based on the group mean data.

3. The mean group estimator suggested by Pesaran and Smith (1995), which involves estimating separate regression for each group and averaging the individual estimates over groups, that is,

$$\hat{\beta}_{MG} = N^{-1}\sum_{i=1}^{N}\hat{\beta}_i \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots..(22)$$

Where $\hat{\beta}_i$ is the OLS estimator of β_i.

1. When T is small (even if N is large); all the procedures yield inconsistent estimators.

2. When both T and N are large, both the cross-section (between) estimator and the mean group estimator yield consistent estimators of $\Phi$and β.

3. The pooled (within) estimator is not consistent for the expected values of β_i and γ_i even when both T and N are large.

To see that the within estimator is inconsistent we rewrite

$$y_{it} = \Phi y_{it-1} + x_{it}\beta + \upsilon_{it} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots..(23)$$

Where $\upsilon_{it} = \varepsilon_{it} + (\lambda_i - \lambda)y_{i,t-1} + x_{it}(\beta_i - \beta)$.

Then it is easily seen that υ_{it} is now correlated with all present and past values of $y_{i,t-1}$ and x_{it-s} for all s ≥ 0. This correlation renders the OLS estimator inconsistent. Furthermore, the fact that υ_{it} is correlated with $y_{i,t-1}$and x_{it-s} for all s $\geq$ 0 rules out the possibility of choosing lagged values of $y_{i,t-1}$ and x_{it} as legitimate instruments. This composite disturbance υ_{it} will also be serially correlated, if x_{it} is serially correlated, as it usually is, and will not be independent of the lagged dependent variable.

This heterogeneity bias, which depends on the serial correlation in the x and the variance of the random parameters, can be quite severe.

3.2.4 Pooled mean group estimation in dynamic heterogeneous panels

To date, there have been three alternative estimation procedures for dynamic panels, differing in the relative magnitudes of N and T.

1. (Small N and large T) When N = 1, the traditional approach was to estimate an autoregressive distributed lag (ARDL) model. For N > 1, the seemingly unrelated regression equation (SURE) procedure is often used. The main attraction of the SURE procedure lies in the fact that it allows the contemporaneous error covariances to be freely estimated. However, this is possible only when N is reasonably small relative to T. When N is of the same order of magnitude as T, the case we are interested in, SURE is not feasible.

2. (Small T and large N) Pesaran and Smith (1995) show that the traditional procedures for estimation of pooled models such as the fixed effects, the random effects, the instrumental

variables (IV) or the Generalized Method of Moments (GMM) estimators can produce inconsistent, and potentially very misleading estimates of the average values of the parameters unless the slope coefficients are homogeneous. In most panels of this sort, however, tests indicate that these parameters differ significantly across groups.

3. (The Bayes and empirical Bayes estimators) Hsiao, Pesaran and Tahmiscioglu (1998) consider Bayes estimation of short-run coefficients in dynamic heterogenous panels, and establish the asymptotic equivalence of the Bayes estimator (Swamy, 1970) and the mean group estimator, showing that the mean group estimator is asymptotically normal for large N and large T so long as ${\sqrt{N}}/{T} \to 0$ as both N and $T \to \infty$.

When both N and T are sufficiently large, there have been two extreme approaches to analyzing dynamic panels. At one extreme are the traditional pooled estimators, such as the fixed and random effects estimators, where only the intercepts are allowed to differ across groups while all other coefficients and error variances are constrained to be the same. At the other extreme, one can estimate separate equations for each group and examine the distribution of the estimated coefficients across groups. Of particular interest is the mean group estimator by Pesaran and Smith (1995).

There are often good reasons to expect the long-run equilibrium relationships between variables to be similar across groups, due to budget or solvency constraints, arbitrage conditions or common technologies influencing all groups in a similar way. However, the reasons for assuming that short-run dynamics and error variances should be the same tend to be less compelling. On this ground Pesaran, Shin and Smith (1999) provide an intermediate estimator called the pooled mean group estimator which involves both pooling and averaging. This estimator allows the intercepts, short-run coefficients and error variances to differ freely across groups, but only the long-run coefficients are constrained to be the same.

We extend the single time series ARDL modelling to the dynamic panel data model,

$$y_{it} = \sum_{j=1}^{p} \lambda_{ij}\, y_{i,t-j} + \sum_{j=0}^{q} x_{i,t-j}\, \sigma_{ij} + \alpha_i + \varepsilon_{it} \;\ldots\ldots\ldots\ldots\ldots (24) \quad , t = 1,2,\ldots,T \quad , \quad \mathrm{i} = 1,2,\ldots ,\mathrm{N}$$

Where $\alpha_i\ represents$ the fixed effects,$x_{i,t}$ is $1 \times\ k$ vector of regressors λ_{ij}, σ_{ij} and are scalar and $1 \times\ k$ vector of parameters. It is convenient to work with the following (unrestricted) error correction form of the above equation

$$\vartriangle y_{it} = \Phi_i y_{i,t-1} + x_{it}\beta_i + \sum_{j=1}^{p-1} \lambda_{ij}^{*} \vartriangle y_{i,t-j} + \sum_{j=1}^{q-1} x_{i,t-j}\, \sigma_{ij}^{*} + \mu_i + \varepsilon_{it} \;\ldots\ldots\ldots\ldots\ldots\ldots .. (25)$$

Where:

$$\Phi_i = -\left(1 - \sum_{j=1}^{p} \lambda_{ij}\right)\ and\ \beta_i = \sum_{j=0}^{q} \sigma_{ij}\ .$$

3.2.2.5 FMOLS and Dynamic OLS methods

In order to check the robustness of the long run relationship in the panel data Fully Modified Ordinary Least Square and Dynamic Ordinary Least square methods are used. Kao, C. and Chiang, M. (2000) clearly explains OLS, FMOLS and DOLS using the Monte Carlo simulations and they fund that the OLS is the most biased estimator for the homogeneous panel, when the serial correlation parameter and the endogeneity parameter are both negative, in almost all cases for the heterogenous panel; the FMOLS is more biased than the OLS for the homogeneous panel and severely biased for the heterogenous panel in almost all trials.

From this especially in the heterogenous panel the failure of the parametric correction is very serious; DOLS performs very well in all cases for both the homogeneous and heterogenous panels. In addition to this adding the number of leads and lags reduces the bias of the DOLS substantially and the sequential limit theory approximates the limit distributions of the DOLS and its t-statistic very well.

In general the relationship between OLS, FMOLS and DOLS can be summarized as the OLS estimator has a non-negligible bias in finite samples; the FMOLS estimator does not improve over the OLS estimator in general and the fully modified (FM) estimator is complicated by the dependence of the correction terms upon the preliminary estimator (here we use OLS), which may be very biased in finite samples with panel data. More seriously, the failure of the non-parametric correction for the FM in panel data could be severe. This indicates that the DOLS estimator may be more promising than the OLS or FMOLS estimators in estimating co-integrated panel regressions.

3.2.2.6 Panel Granger causality test

Panel granger causality test performed to assess the causal link among the variables. There are Granger-causality tests that have been designed to incorporate panel data. Some researchers like Hurlin and Venet (2001) developed a granger causality test for a large number of observations of panel data dimension the test provides both cross-sectional and time series information. Greene (2008) and Baltagi (2005) examines a study and the result shows that the efficiency of Granger causality tests improves when increasing the degrees of freedom and reducing the collinearity among explanatory variables .In addition, Greene (2008) finds that the flexibility of panel data for modeling the behavior of cross-sectional units than conventional time series analysis.

3.2.2.7 Impulse response function and variance decomposition analysis

Impulse response functions show the effects of shocks on the adjustment path of the variables. Forecast error variance decompositions measure the contribution of each type of shock to the forecast error variance. Both computations are useful in assessing how shocks to economic variables reverberate through a system.

I. Impulse Response function

An impulse response function traces the effect of a one-time shock to one of the innovations on current and future values of the endogenous variables. The impulse response function is performed to forecast the relationship between variables for a given time period.

The impulse response function describes as follows:

Let Y_t be a k-dimensional vector series generated by

$$Y_t = A_1 Y_{t-1} + \cdots + A_P Y_{t-p} + U_t \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (26)$$

$$= \Phi(\beta) U_t = \sum_{t=0}^{\infty} \Phi_i U_{t-i} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (27)$$

$$I = (I - A_1\beta - A_2\beta - \cdots - A_P\beta^p)\Phi(\beta) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (28)$$

Where $cov(U_t) = \sum_, \Phi_i$ is the Moving Average coefficient measuring the impulse response. More specifically, $\Phi_{jk,i}$ represents the response of variable j to a unit impulse in variable k occurring i^{th} period ago. IRFs are used to evaluate the effectiveness of a policy change, say increasing rediscount rate.

As Σ is usually non-diagonal, it is impossible to shock one variable with other variables fixed. Some kind of transformation is needed. Cholesky decomposition is the most popular one which we shall turn to now. Let P be a lower triangular matrix such that $\Sigma = PP'$,then eq. (1) can be rewritten as

$$Y_t = \sum_{i=0}^{\infty} \Theta_i \, \omega_{t-i} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(29)$$

Where$\Theta_i = \Phi_i P_, \omega_t = P^{-1} U_t$, and $\mathrm{E}(E(\omega_t \omega_t') = I$. Let D be a diagonal matrix with same diagonals with P and $W = PD^{-1}, \wedge = DD'$. After some manipulations, we obtain

$$\mathrm{Y_t} = \beta_0 \mathrm{Y_t} + \beta_1 \mathrm{Y_{t-1}} + \cdots \beta_p \mathrm{Y_{t-p}} + \mathrm{V_t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(30)$$

Where $\beta_0 = I_k - W^{-1}, W = PD^{-1}, \beta_i = W^{-1} A_i$. Obviously, β_0 is a lower triangular matrix with 0 diagonals. In other words, Cholesky decomposition imposes a recursive causal structure from the top variables to the bottom variables but not the other way around.

When performing an IRF the following should considered:

- ✓ For a K-dimensional stationary VAR (p) process,

$$\Phi_{jk,i} = 0 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(31) \quad , for\ j \neq k, i = 1,2, \ldots$$

is equivalent to

$$\Phi_{jk,i} = 0 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(32)\ , for\ i = 1, \ldots, p(K-1).$$

In other words, if the first pK − p responses of variable j to an impulse in variable k is zero, then all the following responses are all zero.

- ✓ Variable k does not cause variable j if and only if $\Phi_{jk,i} = 0, i = 1,2, \ldots$.

There are Critiques of IRF such as Sensitive to variables ordering. Because of this and other criticisms a generalized impulse response function developed by Pesaran offers a partial solution and Granger and Swanson (1997) proposed a different but more promising one and omitting important variables may lead to major distortions in IRF and make the empirical results worthless. However, its impact on forecasting could small.

II. Variance Decomposition

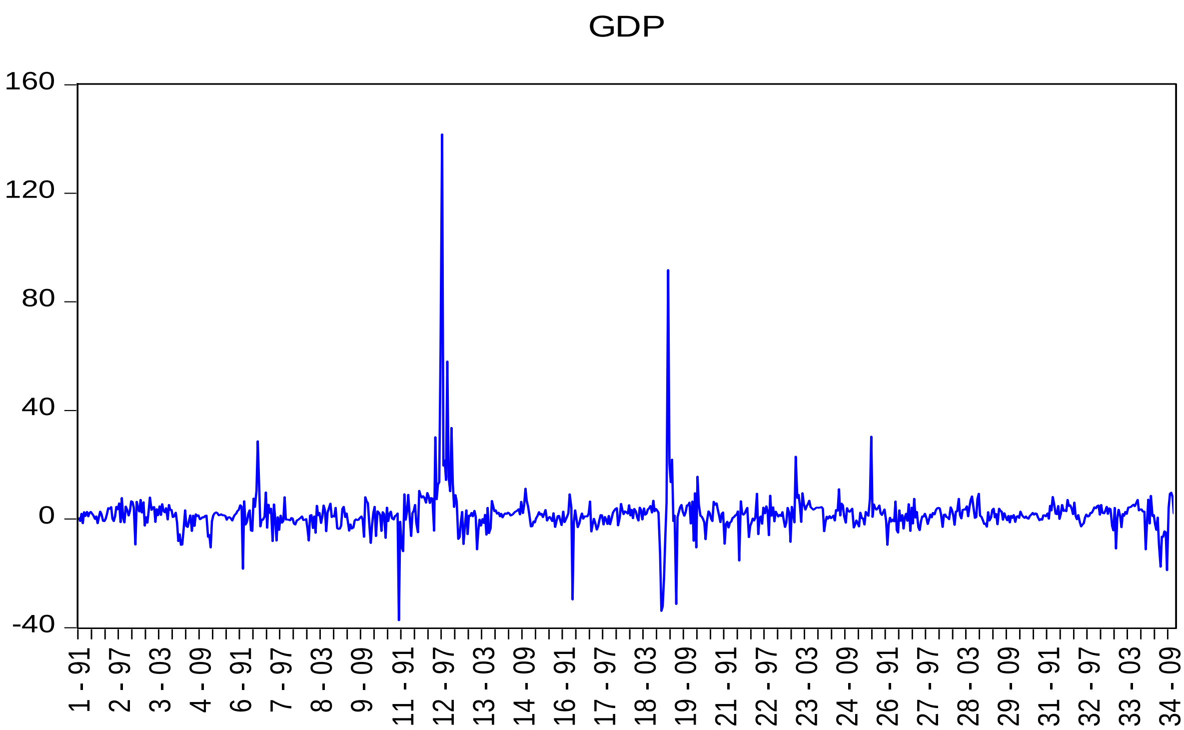
It separates the variation in an endogenous variable into the component shocks to the VAR. In other words, the variance decomposition provides information about the relative importance of each random innovation in affecting the variation of the variables in the VAR.

CHAPER FOUR

4. Data Analysis and interpretation

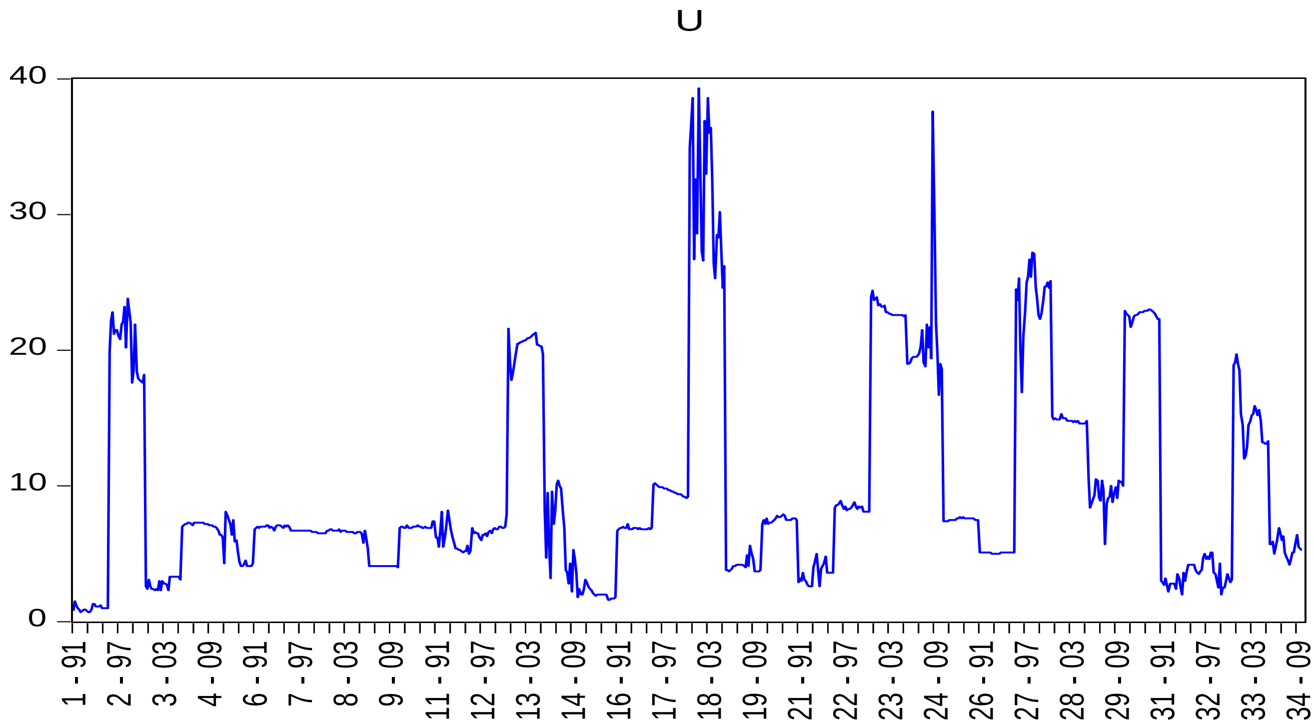
4.1. Distributive analysis

Figure 1.Trends of GDP percapita growth in 34 Su-Sahara African countries from 1991-2014



The GDP per capita in 34 sub Saharan Africa countries shows that there are fluctuations between countries with in time periods. That means there is high GDP per capita in some countries but recession (negative) economic growth in some others. For example, Countries like GDP per capita in Equatorial Guinea, 1997 recorded GDP per capita is 142 and Liberia in the same year but the lower recorded is in Central Africa Republic in 2013 the amount is -37 and in Liberia in 1992 the amount is -34.

Figure 2.Trends of Unemployment in 34 Sub-Sahara African Countries From 1991-2014



The above figure shows that unemployment in 34 sub-Sahara African countries fluctuating between time periods 1991-2014.There are countries that have extremely high unemployment in some countries and there are countries that have lower unemployment rate . That means there are counties unemployment is a serious problem and countries that are unemployment is not a serious issue. The highest unemployment is recorded in Lesotho in 1993, 1997 and 2003 the amount is 39 and in Namibia 2008 the amount recorded was 38. The lowest unemployment recorded in Benin almost in over the time period and Guinea in 2013 the amount recorded was 2.

4.2. Empirical Analysis

4.2.1. Lag Selection Criteria

For any VAR model appropriate lag selection is a start for the process. The correct lag length selection is essential for panel VAR, having lags which are too short fails to capture the system's dynamics and which leads to omitted variable bias on the other hand having too many lags causes a loss of degrees of freedom which results in over-parameterization .Based on the VAR lag selection criteria table 4.1 below shows that lag 4 is selected as a lag that should be included in the model.

Table 1.VAR Lag Order Selection Criteria Result

VAR Lag Order Selection Criteria

Endogenous variables: GDP U FDI

G

Exogenous variables: C

Date: 06/26/16 Time: 15:36

Sample: 1991 2014

Included observations: 678

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-8027.503	NA	228716.9	23.69175	23.71841	23.70207
1	-6015.540	3994.250	634.2524	17.80395	17.93726	17.85556
2	-5349.434	1314.528	93.19880	15.88624	16.12619	15.97913
3	-4855.308	969.3038	22.74500	14.47583	14.82244	14.61001
4	-4767.966	170.3050*	18.42888*	14.26538*	14.71863*	14.44085*

* indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

4.2.2. Panel Unit root test results

Non-Stationarity of time series data has often been regarded as a problem in empirical analysis. Working with non-stationary variables leads to spurious regression results, from which further inference is meaningless. Hence, the first step in time series econometric analysis is to carry out unit root test on the variables of interest. In the same manner in panel data non stationarity of data has often been regarded as a problem in the empirical work, so in the panel data analysis panel unit root test is the first step for the variables under investigation .The test examines whether the data series is stationary or not. To conduct the test, Levin, Lin & Chu t, Breitung t-stat, Im, Pesaran and Shin W-stat, ADF - Fisher Chi-square and PP - Fisher Chi-square is used with and without a trend at both level and first difference. The null hypothesis in these tests is that the series under investigation has unit root. On the other hand, the alternative hypothesis is that the series is stationary.

After lag selection the researcher checks the unit roots of the variables under investigation, so from the annex 1 that GDP per capita, population growth and FDI, net inflow are stationary at level. But unemployment rate is not stationary at level but results from Annex 2 shows that when it converts in to first difference becomes stationary.

4.2.3. Model stability

After running the unrestricted VAR model regression at the selected lag i.e, lag four the result in table 2 and figure 3 shows that there is no any root lies outside of the unit circle from this the model is stable at lag four. Stability implies that the panel VAR is invertible and has an infinite order moving average representation, providing known interpretation to estimated impulse response and variance decompositions.

Figure 3. Model Stability Result

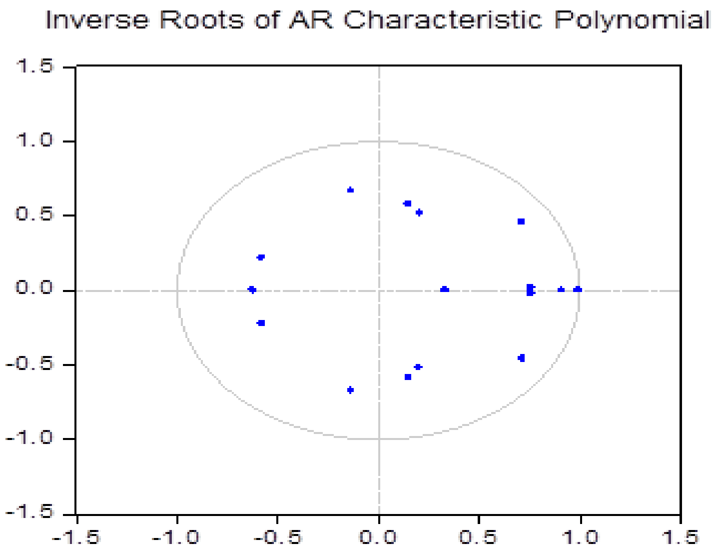


Table 2.Model Stability result

Roots of Characteristic Polynomial
Endogenous variables: GDP U FDI G
Exogenous variables: C
Lag specification: 1 4
Date: 07/10/16 Time: 21:14

Root	Modulus
0.993020	0.993020
0.914881	0.914881
0.713887 - 0.456454i	0.847340
0.713887 + 0.456454i	0.847340
0.759179 - 0.018678i	0.759409
0.759179 + 0.018678i	0.759409
-0.137354 - 0.669662i	0.683603
-0.137354 + 0.669662i	0.683603
-0.621514	0.621514
-0.578423 - 0.220918i	0.619175
-0.578423 + 0.220918i	0.619175
0.151030 - 0.581732i	0.601018
0.151030 + 0.581732i	0.601018
0.204772 - 0.518189i	0.557182
0.204772 + 0.518189i	0.557182
0.332914	0.332914

No root lies outside the unit circle.
VAR satisfies the stability condition.

4.2.4. Panel co-integration test

The panel unit root test demonstrated that all variables are not stationary at level. This implies that any estimation using this level data will lead to wrong conclusion and policy implication. However, the Granger representation theorem states that it is possible for non-stationary variables to produce a stationary relationship if they are co-integrated. This would imply that there is a meaningful long run relationship among the variables. Thus, the presence of co-integration between variables is checked using pedroni and Kao Residual co-integration tests.

From Annex 3 the result from the panel co-integration tests that are Pedroni Residual co-integration tests and Kao Residual co-integration test shows that there is co-integration from GDP per capita to unemployment rate .From this results we concluded that the two variables have long run relationship in sub Saharan African countries.

But from annex 4 the entire pedroni test results shows that there is no co – integration from unemployment to GDP in this case, where GDP per capita and other variables become dependent and unemployment rate become independent. But the Kao residul co integration test shows that there is co integration which means there is long run relationship between unemployment and economic growth. But the relationship in this side is weak.

4.2.5. Pooled Mean Group Regression (PMG) estimation

From Table 3 below estimation we can verify that Unemployment and economic growth has a negative relationship in the long run in sub - Sahara African countries. The result shows that one unit increase in the unemployment rate leads to 0.15 unit decrease in the GDP per capita growth. FDI, net inflow rate have positive relationship with GDP per capita in the long run that is a one unit increase in FDI leads to 0.519 unit increase in GDP per capita and population growth have negative relationship with GDP per capita in the long run that is a one unit increase in the population growth leads to 3.411 unit decrease in GDP per capita in the Sub-Saharan Africa countries.

From the same table the Short run relationships between GDP per capita and unemployment is significant only on the first difference and at lag one periods. Form this we conclude that short run relationship between GDP per capita and unemployment rate is weak.

Table 3.Poooled Mean Regression Estimation results

Dependent Variable: D(GDP)
Method: ARDL
Date: 06/26/16 Time: 15:29
Sample: 1995 2014
Included observations: 678
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): U FDI G
Fixed regressors: C
Number of models evalulated: 16
Selected Model: ARDL(4, 4, 4, 4)
Note: final equation sample is larger than selection sample

Variable	Coefficient	t-Statistic	Prob.*
Long Run Equation			
U	-0.152	-18.739	0.000*
FDI	0.519	56.864	0.000*
G	-3.411	-199.744	0.000*

Short Run Equation

Co-integration equation 01	-1.708	-2.838	0.005*
D(GDP(-1))	0.378	0.722	0.471
D(GDP(-2))	0.137	0.376	0.707
D(GDP(-3))	-0.068	-0.324	0.747
D(U)	-12.094	-2.688	0.008*
D(U(-1))	-18.556	-2.166	0.031**
D(U(-2))	-1.088	-0.183	0.855
D(U(-3))	1.907	0.215	0.830
D(FDI)	0.188	0.288	0.774
D(FDI(-1))	-0.579	-1.714	0.088***
D(FDI(-2))	-0.134	-0.346	0.730
D(FDI(-3))	-0.445	-1.977	0.049**
D(G)	-201.622	-1.834	0.068***
D(G(-1))	438.939	1.836	0.068***
D(G(-2))	-443.623	-1.775	0.077***
D(G(-3))	189.602	1.768	0.078***
Constant	17.489	2.727	0.007*

Note *, **, *** shows Significant level at 1%, 5% and 10% respectively

4.2.6. Fully modified OLS and Dynamic OLS

From table 4 below the FMOLS test result shows that there is negative relationship between unemployment and economic growth in the long run. A one unit increase in the unemployment rate leads to 1.69 unit decrease in the economic growth. But this result shows that population growth positively affected the economic growth. It has a significant influence a one unit increase in population growth leads to 3.362 increases in the economic growth. FDI also has positively related to GDP per capita that is a one unit increase FDI leads to 0.315 unit increases in GDP per capita.

Table 4.Pannel Fully Modified Least Square Test Results

Dependent Variable: GDP

Method: Panel Fully Modified Least Squares (FMOLS)

Date: 06/26/16 Time: 15:32
Sample (adjusted): 1992 2014
Periods included: 23
Cross-sections included: 34

Total panel (unbalanced) observations: 780

Panel method: Grouped estimation
Long-run covariance estimates (Bartlett kernel, Newey-West fixed bandwidth)

Variable	Coefficient	t-Statistic	Prob.
U	-1.686	-5.472	0.000
FDI	0.315	3.583	0.000
G	3.362	4.467	0.000

From table 5 below the results of DOLS shows that unemployment and economic growth have negative relationship. A one unit increase in unemployment leads to 1.77 unit reduction in GDP per capita (economic growth). FDI has a positive relationship with economic growth. A unit increase in FDI leads to 0.213 unit increase in economic growth. Population growth rate have influence the economic growth positively. A one unit increase in the population growth leads to 3.74 units increase in economic growth.

Table 5.Panel Dynamic OLS test Results

Dependent Variable: GDP
Method: Panel Dynamic Least Squares (DOLS)
Date: 06/24/16 Time: 09:02
Sample: 1991 2014
Periods included: 24
Cross-sections included: 34
Total panel (unbalanced) observations: 814
Panel method: Grouped estimation
Static OLS leads and lags specification
Long-run variances (Bartlett kernel, Newey-West fixed bandwidth) used for individual coefficient covariances

Variable	Coefficient	t-Statistic	Prob.
U	-1.770	-4.363	0.000
FDI	0.213	1.816	0.070
G	3.737	3.702	0.000

4.2.6. Panel Granger causality test results

Results of the Panel granger causality test table 6 below shows that unemployment granger causes GDP per Capita and GDP per capita granger causes unemployment in Sub-Saharan Countries. This implies that there is a bi directional relationship between unemployment and economic growth. FDI granger causes GDP per capita in these countries. Population growth causes GDP and also GDP per capita growth granger causes population growth. This implies that there is a bidirectional relationship between GDP per capita growth and population growth in sub Sub-Saharan Africa countries. Population growth causes unemployment and also unemployment causes population growth. From this we can say that there is a bidirectional relationship between unemployment and economic growth in given countries. Population growth granger causes FDI and also FDI granger causes Population growth in Sub Sahara African countries.

Table 6.Panel Granger Causality Test results

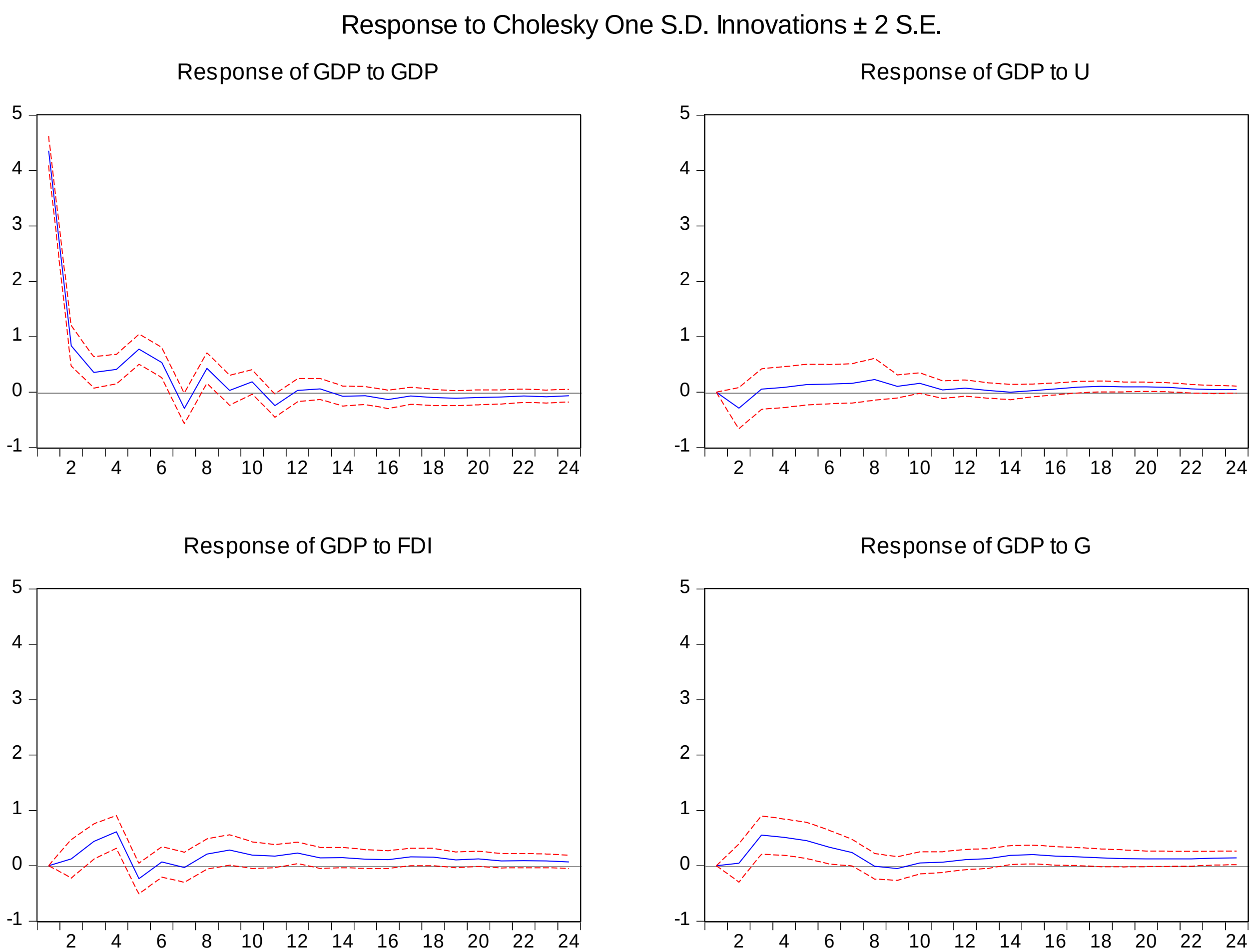
Pairwise Dumitrescu Hurlin Panel Causality Tests
Date: 06/26/16 Time: 15:48
Sample: 1991 2014
Lags: 4

Null Hypothesis:	W-Stat.	Zbar-Stat.	Prob.
U does not homogeneously cause GDP	7.578	3.323	0.001
GDP does not homogeneously cause U	7.241	2.911	0.004
FDI does not homogeneously cause GDP	9.950	6.233	0.000
GDP does not homogeneously cause FDI	5.158	0.323	0.747
G does not homogeneously cause GDP	8.423	4.374	0.000
GDP does not homogeneously cause G	6.831	2.404	0.016
FDI does not homogeneously cause U	5.690	0.980	0.327
U does not homogeneously cause FDI	7.007	2.604	0.009
G does not homogeneously cause U	10.912	7.455	0.000
U does not homogeneously cause G	7.768	3.563	0.000
G does not homogeneously cause FDI	12.044	8.815	0.000
FDI does not homogeneously cause G	6.671	2.190	0.029

4.2.7. Impulse response function results

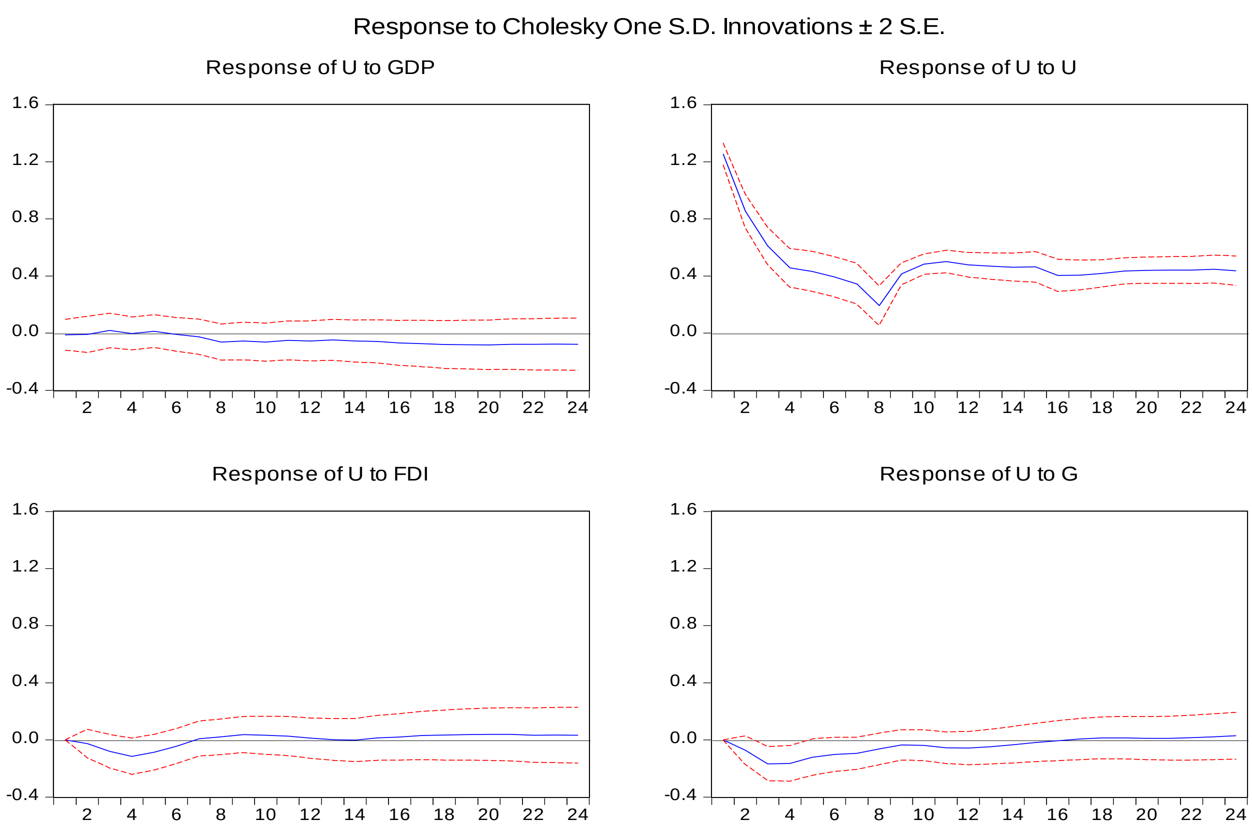
The impulse response functions determine the transmission of the shock in the economic variables. Accordingly, figure 4 and annex 5A show the results of the impulse response functions a one unit standard deviation shock to other variables result on GDP for next 24 years. A one unit shock to GDP results a positive shock on its own up to 13 years but a negative shock after that. A unit standard deviation shock to unemployment results in a negative shock in the second year and a positive shock after that. A one unit standard deviation shock to FDI results in a positive shock to GDP per capita up to the fourth year but a negative shock in the fifth year and a positive shock starting from the sixth year. A one unit standard deviation shock in population growth results in appositive shock to GDP per capita for the next 24 years.

Figure 4.Impluse response function result of GDP



Similarly, figure 5 and annex 5B shows the results of the impulse response functions on a one unit standard deviation shock on other variables to unemployment. A one standard deviation shock to GDP results in a negative shock to unemployment, which is similar to the Okun's law that is unemployment, is negatively related to economic growth .A one standard deviation shock to unemployment results in a positive shock to unemployment, which is own shock. A one unit standard deviation shock to FDI results in a negative shock to unemployment up to the sixth year and become positive up to 13th years and become positive. A unit shock to population growth results in a negative shock to unemployment up to the 16th years but starting from the 17th year a shock to population growth results in a positive shock to unemployment.

Figure 5. Impulse response function Result of Unemployment



4.2.8. Variance Decomposition Results

The variance decomposition provides information about the relative importance of each random innovation in affecting the variation of the variables in the VAR. In this case the researcher assumes checking what happen on the short run, which is the third year and the long run, which is the twenty fourth year the variation of GDP per capita and unemployment rate.

Accordingly, figure 6 and annex 6A show the variance decomposition of GDP on the 24 years' time horizon. So, in the short run a Shock to GDP accounts for 82.75 % variation in fluctuations to GDP, which is own shock, shock to unemployment can cause 0.047% fluctuations on GDP, shock to FDI can cause 12.075% fluctuations in GDP and shock to population growth can cause 5.12% of fluctuations to GDP. In the long run a shock to GDP accounts for 71.21% variation in the fluctuation of GDP ,which is own shock , shock to unemployment can cause 0.161% fluctuations in GDP, shock to FDI can cause 14.45% of fluctuations in GDP and shock to population growth can contribute 14.18 % of fluctuation in GDP. This result shows that shock to unemployment cannot contribute much to the fluctuation of GDP neither to the short run nor to the long run periods but FDI and population growth can contribute much in the fluctuation of GDP in the short run as well as in the long run periods.

Figure 6. Variance Decomposition Result of GDP

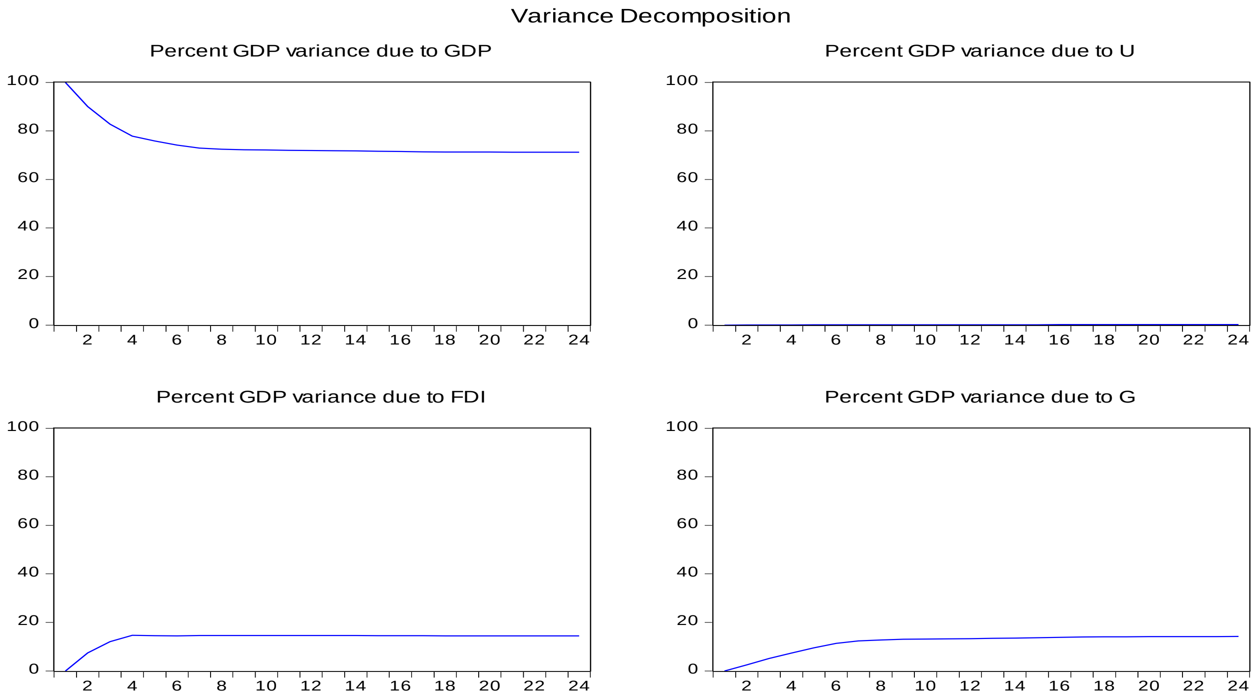
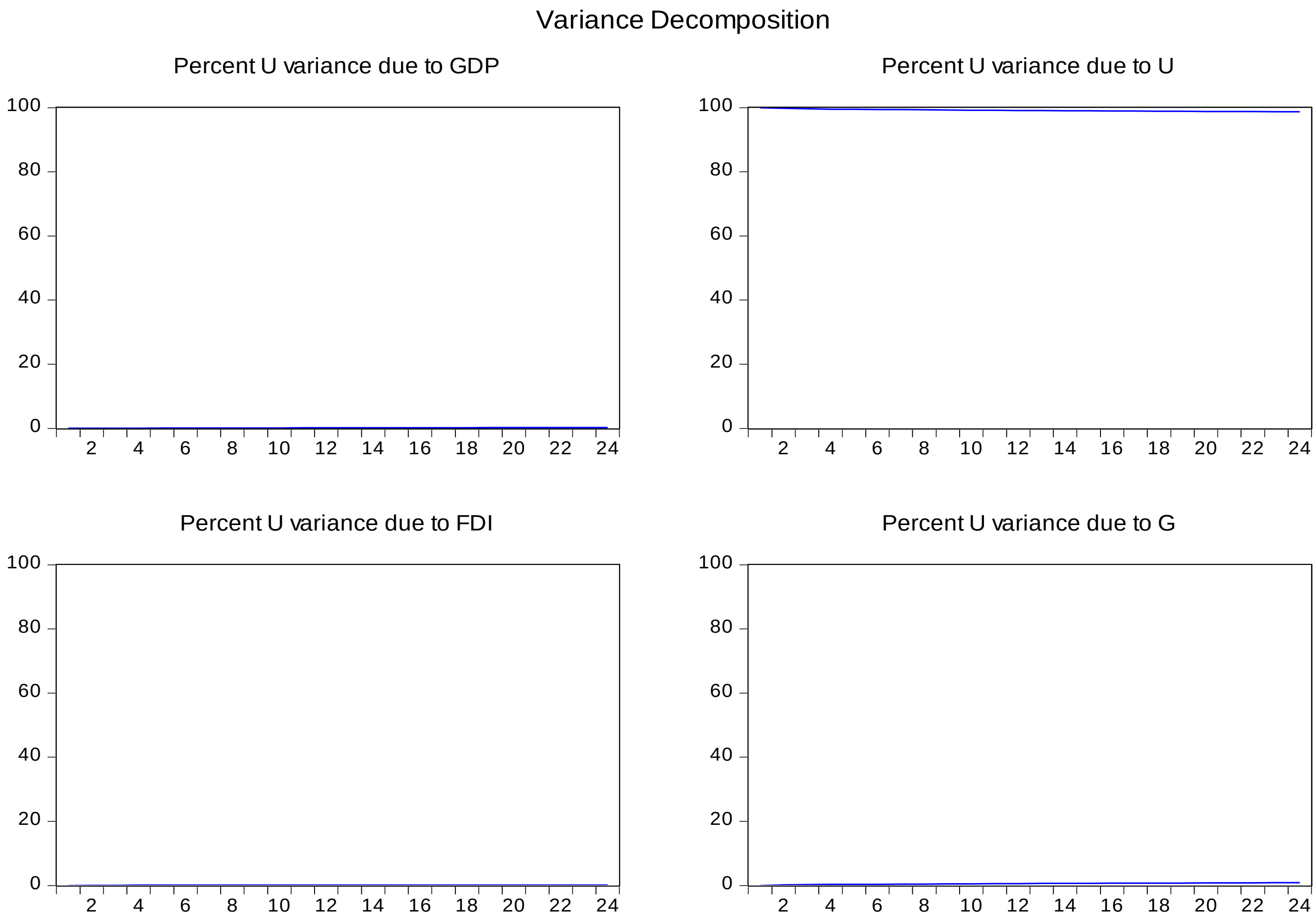


Figure 7. Variance Decomposition Result of Unemployment



Similarly, figure 7 and annex 6B show the variance decomposition of unemployment on the 24 time horizon. So, in the short run a shock to GDP accounts for 0.0615 % of fluctuations to unemployment, shock to unemployment can cause 99.65% of fluctuations to unemployment, own shocks, shock to FDI can cause 0.0226% 0f fluctuations in unemployment and shock to population growth can cause 0.2628% of fluctuations to unemployment. In the long run a shock to GDP accounts for 0.266% of fluctuation to unemployment, shock to unemployment can cause 98.726% to fluctuations to unemployment, which is own shocks, shock to FDI can cause 0.128% of fluctuations to unemployment and shock to population growth can contribute 0.87966 % of fluctuation to unemployment. This result shows that shock to GDP cannot contribute much to the fluctuation of unemployment neither to the short run nor to the long run periods and the same to FDI and population growth can not contribute much in the fluctuation of unemployment in the short run as well as in the long run time periods. But shock to unemployment has much contribution in the fluctuation of unemployment in the short run as well as in the long run time periods.

CHAPTER FIVE

5. Conclusion and recommendation

5.1 Conclusions of the study

This paper examines the relationship between economic growth and unemployment in Sub-Saharan African Countries empirically. The empirical study is conducted using a PVAR approach using data of 34 SSA Countries between the periods 1991 to 2014.

The panel granger causality experimental results of this study confirm that, there is bidirectional relationship between GDP per capita and unemployment; GDP per capita and population growth however, there is a unidirectional relationship between GDP per capita and FDI (i.e., FDI granger causes GDP per capita growth). There is a bi directional relationship between Population growth and unemployment and also FDI and Population growth but there is a unidirectional relationship between FDI and unemployment i.e., unemployment granger causes FDI in Sub-Sahara African countries.

The PMG estimation result shows that there is negative relationship between unemployment and economic growth in the long run in SSA countries. FDI has a positive relationship with the GDP per capita but population has a negative relationship with GDP per capita. However, the short run relationships between GDP per capita and unemployment is negative but significant only on the first difference and at lag one periods but population growth and FDI, net inflow has no relationship with GDP per capita in the short run.

The FMOLS and DOLS results shows that there is negative relationship between GDP per capita and unemployment and positive relationship between FDI and GDP per capita in the long run. But in contrast to the PMG test result the relationship between GDP per capita and population growth has a positive relationship which means increase in population leads to increase in GDP per capita growth in Sub Saharan African countries. The PMG, FMOLS and DOLS results shows that there is negative relationship between unemployment and economic growth but when we camper the effect of economic growth on unemployment in SSA countries with the Okuns 1976 study results in USA the effect in SSA countries is minimal.

The Impulse response function result shows that a one unit standard deviation shock to GDP per capita results in a positive shock to its own up to the 13th years after that it results a negative shock .From this we can conclude that it needs transformation of the economy after the next 13 years but if it is continue in the existing trend the GDP per capita negatively affects by its own shock. A one unit standard deviation shock to unemployment positively affects the GDP per capita in these countries for the next 24 years. This implies that unemployment has no negative effect on the economic growth of the countries or unemployment is not a problem in the Sub Saharan countries. A one unit standard deviation shock to FDI results to a positive shock to GDP per capita. This implies that the SSA countries should attract more FDI to increase the GDP per capita growth. A one unit standard deviation shock to population growth results in an increase in economic growth. This implies that there is a direct relationship between population growth and economic growth. The result found in this paper favors the Simon Kuznets and Boserup's argument which states that population growth has a positive impact on economic growth.

The variance decomposition result shows that the shock of the on economic growth has no more impact on unemployment and also the shock on unemployment has on much impact on the economic growth.

5.2 Recommendation

The study has provided empirical evidences on the relationship between unemployment and economic growth in SSA Countries. Based on the findings reported in the preceding section, the study recommends the following:

First ,Since GDP per capita growth affects negatively unemployment in the region there should be design policies that foster the GDP per capita growth to reduce unemployment. But the variance decomposition result shows that the effect of the GDP per capita growth for the reduction of the unemployment is minimal to increase the effect investing on the sectors that are loubor intensive such as manufacturing, agricultural and other sectors and also improve the productivity & linkage with other sectors through value chain development for agriculture sector & other policies for other sectors to the stimulate investment & to increase employment opportunities in the region. Second, Since GDP per capita growth and FDI has a positive relationship this result shows that the increase in FDI leads to an increase in economic growth this leads to the reduction in unemployment. Hence, SSA countries should design appropriate policies to attract more FDI to the region. Third, the relationship between GDP and population growth is positive in the long run. Therefore, SSA countries should design a quality education system to benefit from the growing population.

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Annex

Annex 1.Panel Unit Root test results at level.

Series: GDP

Date: 06/26/16 Time: 15:05

Sample: 1991 2014

Exogenous variables: None

User-specified lags: 4

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*	-4.73843	0.0000	34	646
Null: Unit root (assumes individual unit root process)				
ADF - Fisher Chi-square	112.838	0.0005	34	646
PP - Fisher Chi-square	445.330	0.0000	34	782

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

Panel unit root test: Summary

Series: U

Date: 06/26/16 Time: 15:07

Sample: 1991 2014

Exogenous variables: None

User-specified lags: 4

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*	-2.41983	0.0078	34	646
Null: Unit root (assumes individual unit root process)				
ADF - Fisher Chi-square	70.3051	0.4003	34	646
PP - Fisher Chi-square	82.1329	0.1164	34	782

** 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: 06/26/16 Time: 15:08

Sample: 1991 2014

Exogenous variables: None

User-specified lags: 4

Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-2.05306	0.0200	34	644
Null: Unit root (assumes individual unit root process)				
ADF - Fisher Chi-square	58.3848	0.7907	34	644
PP - Fisher Chi-square	176.391	0.0000	34	780

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

Panel unit root test: Summary

Series: G

Date: 06/26/16 Time: 15:09

Sample: 1991 2014

Exogenous variables: None

User-specified lags: 4

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*	-2.89869	0.0019	34	646
Null: Unit root (assumes individual unit root process)				
ADF - Fisher Chi-square	66.7009	0.5219	34	646
PP - Fisher Chi-square	110.363	0.0009	34	782

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

Annex 2.Panel Unit Root Test Results at First Differences.

Panel unit root test: Summary

Series: D(GDP)

Date: 06/26/16 Time: 15:13

Sample: 1991 2014

Exogenous variables: None

User-specified lags: 4

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*	-18.0220	0.0000	34	612
Null: Unit root (assumes individual unit root process)				
ADF - Fisher Chi-square	326.978	0.0000	34	612
PP - Fisher Chi-square	910.057	0.0000	34	748

** 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(U)

Date: 06/26/16 Time: 15:14

Sample: 1991 2014

Exogenous variables: None

User-specified lags: 4

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*	-10.9938	0.0000	31	558
Null: Unit root (assumes individual unit root process)				
ADF - Fisher Chi-square	204.176	0.0000	31	558
PP - Fisher Chi-square	808.229	0.0000	31	682

** 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(FDI)

Date: 06/26/16 Time: 15:16

Sample: 1991 2014

Exogenous variables: None

User-specified lags: 4

Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-14.4272	0.0000	34	610
Null: Unit root (assumes individual unit root process)				
ADF - Fisher Chi-square	287.410	0.0000	34	610
PP - Fisher Chi-square	845.537	0.0000	34	746

** 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(G)

Date: 06/26/16 Time: 15:16

Sample: 1991 2014

Exogenous variables: None

User-specified lags: 4

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*	-11.0667	0.0000	34	612
Null: Unit root (assumes individual unit root process)				
ADF - Fisher Chi-square	239.245	0.0000	34	612
PP - Fisher Chi-square	201.659	0.0000	34	748

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

Annex 3.Panel Co-integration Test Results when GDP is Dependent Variable

Pedroni Residual Cointegration Test

Series: GDP U FDI G

Date: 06/26/16 Time: 15:19

Sample: 1991 2014

Included observations: 816

Cross-sections included: 34

Null Hypothesis: No cointegration

Trend assumption: No deterministic intercept or trend

User-specified lag length: 4

Newey-West automatic bandwidth selection and Bartlett kernel

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

			Weighted	
	Statistic	Prob.	Statistic	Prob.
Panel v-Statistic	1.687623	0.0457	-1.430905	0.9238
Panel rho-Statistic	-5.734254	0.0000	-7.329741	0.0000
Panel PP-Statistic	-15.41216	0.0000	-13.66373	0.0000
Panel ADF-Statistic	-4.094734	0.0000	0.037127	0.5148

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

	Statistic	Prob.
Group rho-Statistic	-6.279212	0.0000
Group PP-Statistic	-20.15789	0.0000
Group ADF-Statistic	0.366761	0.6431

Cross section specific results

Pedroni Residual Cointegration Test

Series: GDP U FDI G

Date: 06/26/16 Time: 15:23

Sample: 1991 2014

Included observations: 816

Cross-sections included: 34

Null Hypothesis: No cointegration

Trend assumption: No deterministic trend

User-specified lag length: 4

Newey-West automatic bandwidth selection and Bartlett kernel

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

			Weighted	
	Statistic	Prob.	Statistic	Prob.
Panel v-Statistic	1.979712	0.0239	-2.618215	0.9956
Panel rho-Statistic	-4.619082	0.0000	-5.996419	0.0000
Panel PP-Statistic	-15.80548	0.0000	-16.53304	0.0000
Panel ADF-Statistic	0.162595	0.5646	1.836742	0.9669

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

	Statistic	Prob.
Group rho-Statistic	-4.010351	0.0000
Group PP-Statistic	-20.91268	0.0000
Group ADF-Statistic	2.570228	0.9949

Cross section specific results

Kao Residual Cointegration Test

Series: GDP U FDI G

Date: 06/26/16 Time: 15:24

Sample: 1991 2014

Included observations: 816

Null Hypothesis: No cointegration

Trend assumption: No deterministic trend

User-specified lag length: 4

Newey-West automatic bandwidth selection and Bartlett kernel

	t-Statistic	Prob.
ADF	3.425807	0.0003
Residual variance	88.80834	
HAC variance	21.50348	

Annex 4.Panel Co-integration test results When Unemployment is Dependent variable

Pedroni Residual Cointegration Test

Series: U GDP FDI G

Date: 06/26/16 Time: 17:10

Sample: 1991 2014

Included observations: 816

Cross-sections included: 34

Null Hypothesis: No cointegration

Trend assumption: No deterministic intercept or trend

User-specified lag length: 4

Newey-West automatic bandwidth selection and Bartlett kernel

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

			Weighted	
	Statistic	Prob.	Statistic	Prob.
Panel v-Statistic	-3.911742	1.0000	-5.032014	1.0000
Panel rho-Statistic	0.515003	0.6967	1.878246	0.9698
Panel PP-Statistic	-1.485111	0.0688	0.750932	0.7737
Panel ADF-Statistic	1.915388	0.9723	1.709991	0.9564

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

	Statistic	Prob.
Group rho-Statistic	3.414980	0.9997
Group PP-Statistic	0.182419	0.5724
Group ADF-Statistic	3.584878	0.9998

Kao Residual Cointegration Test

Series: U GDP FDI G

Date: 06/26/16   Time: 17:11

Sample: 1991 2014

Included observations: 816

Null Hypothesis: No cointegration

Trend assumption: No deterministic trend

User-specified lag length: 4

Newey-West automatic bandwidth selection and Bartlett kernel

	t-Statistic	Prob.
ADF	-1.826689	0.0339
Residual variance	2.062128	
HAC variance	1.498131	

Annex 5.Impulse response function Results

A) Response of GDP to Cholesky (d.f. adjusted) one S.D. Innovations

Period	GDP	U	FDI	G
1	7.004336	0.000000	0.000000	0.000000
2	1.409195	-0.134073	2.055746	1.193262
3	0.372465	0.106577	1.800752	1.320868
4	0.702341	0.134574	1.512616	1.317507
5	0.963504	0.152268	-0.579351	1.307645
6	0.293208	0.065340	0.418176	1.199351
7	0.118972	0.098566	0.546767	0.925479
8	0.363278	0.070320	0.304666	0.640822
9	0.150476	0.067783	0.097107	0.461337
10	0.090055	0.057884	0.180612	0.322206
11	0.111725	0.062040	0.166064	0.262257
12	0.111342	0.056354	0.048527	0.270674
13	0.027640	0.055518	0.057764	0.311037
14	-0.006276	0.054892	0.049858	0.342351
15	-0.013951	0.051413	0.023575	0.355174
16	-0.038832	0.044993	0.005011	0.344595
17	-0.052917	0.038648	0.012984	0.309131
18	-0.049980	0.032501	0.012467	0.259856
19	-0.042778	0.026598	0.006658	0.210004
20	-0.039530	0.021640	0.007133	0.168615
21	-0.034093	0.017984	0.007366	0.139742
22	-0.029363	0.015115	0.004523	0.124245
23	-0.028372	0.012774	0.001429	0.119004
24	-0.029264	0.010703	0.000123	0.118832

Cholesky Ordering: GDP U FDI G

B) Response of U to Cholesky (d.f. adjusted) one S.D. Innovations

Period	GDP	U	FDI	G
1	-0.012429	1.255607	0.000000	0.000000
2	-0.009644	0.854307	-0.026399	-0.072477
3	0.018087	0.610852	-0.080289	-0.167169
4	-0.002348	0.456474	-0.115375	-0.164692
5	0.012810	0.432070	-0.086706	-0.121051
6	-0.009865	0.394121	-0.044120	-0.102031
7	-0.026302	0.344665	0.008226	-0.093774
8	-0.062459	0.193200	0.021372	-0.062984
9	-0.055771	0.415287	0.037107	-0.035556
10	-0.063441	0.482088	0.032014	-0.038433
11	-0.051380	0.501650	0.026807	-0.055515
12	-0.055592	0.478421	0.011885	-0.057626
13	-0.047552	0.468543	0.002241	-0.047641
14	-0.055687	0.461954	-0.001531	-0.033615
15	-0.058507	0.463733	0.013753	-0.018776
16	-0.069038	0.404754	0.020908	-0.005692
17	-0.073198	0.405795	0.030575	0.005951
18	-0.080635	0.418545	0.033816	0.014228
19	-0.080937	0.435650	0.037923	0.014682
20	-0.082550	0.440124	0.038871	0.011665
21	-0.078275	0.441902	0.038109	0.011354
22	-0.078838	0.441756	0.033275	0.015535
23	-0.077388	0.447707	0.033336	0.022183
24	-0.078670	0.436936	0.032491	0.029218

Cholesky Ordering: GDP U FDI G

Annex 6.Variance Decomposition Results

A) Variance Decomposition of GDP

Period	S.E.	GDP	U	FDI	G
1	7.004336	100.0000	0.000000	0.000000	0.000000
2	7.530902	90.00618	0.031695	7.451522	2.510599
3	7.864603	82.75447	0.047427	12.07528	5.122820
4	8.147834	77.84416	0.071466	14.69682	7.387555
5	8.329725	75.81959	0.101795	14.54573	9.532883
6	8.431362	74.12358	0.105361	14.44315	11.32791
7	8.501012	72.93354	0.117086	14.62113	12.32825
8	8.538594	72.47393	0.122840	14.62002	12.78321
9	8.553192	72.25771	0.128701	14.58305	13.03054
10	8.561833	72.12299	0.133012	14.59812	13.14587
11	8.568412	72.02929	0.138050	14.61328	13.21938
12	8.573731	71.95680	0.142199	14.59836	13.30265
13	8.579790	71.85625	0.146186	14.58228	13.41529
14	8.586940	71.73669	0.150029	14.56138	13.55191
15	8.594480	71.61114	0.153344	14.53659	13.69892
16	8.601592	71.49480	0.155827	14.51260	13.83677
17	8.607404	71.40206	0.157632	14.49323	13.94708
18	8.611541	71.33684	0.158905	14.47952	14.02474
19	8.614252	71.29443	0.159759	14.47047	14.07535
20	8.616022	71.26723	0.160324	14.46459	14.10786
21	8.617245	71.24857	0.160714	14.46056	14.13015
22	8.618205	71.23386	0.160986	14.45736	14.14779
23	8.619083	71.22044	0.161173	14.45442	14.16397
24	8.619958	71.20712	0.161294	14.45149	14.18010

Cholesky Ordering: GDP U FDI G

B) Variance Decomposition of U

Period	S.E.	GDP	U	FDI	G
1	7.004336	0.011435	99.98857	0.000000	0.000000
2	7.530902	0.019695	99.78011	0.028162	0.172030
3	7.864603	0.061529	99.65303	0.022622	0.262819
4	8.147834	0.056519	99.53597	0.089101	0.318408
5	8.329725	0.078940	99.49715	0.092240	0.331665
6	8.431362	0.090786	99.45063	0.098789	0.359799
7	8.501012	0.116513	99.38750	0.099079	0.396909
8	8.538594	0.123565	99.33598	0.099172	0.441279
9	8.553192	0.138876	99.27459	0.103371	0.483160
10	8.561833	0.152455	99.21834	0.106870	0.522333
11	8.568412	0.166316	99.16594	0.110332	0.557413
12	8.573731	0.177422	99.12119	0.111663	0.589723
13	8.579790	0.188021	99.07941	0.113871	0.618700
14	8.586940	0.197609	99.04092	0.116046	0.645420
15	8.594480	0.206332	99.00496	0.118045	0.670664
16	8.601592	0.214516	98.97031	0.119640	0.695536
17	8.607404	0.222248	98.93637	0.121104	0.720277
18	8.611541	0.229546	98.90304	0.122437	0.744972
19	8.614252	0.236485	98.87050	0.123619	0.769396
20	8.616022	0.243118	98.83888	0.124701	0.793299
21	8.617245	0.249421	98.80849	0.125694	0.816393
22	8.618205	0.255369	98.77951	0.126609	0.838508
23	8.619083	0.260984	98.75198	0.127456	0.859582
24	8.619958	0.266283	98.72581	0.128246	0.879662

Cholesky Ordering: GDP U FDI G

Annex 7.List of Sub-Sahara African Countries included in the study

1	Benin	18	Lesotho
2	Botswana	19	Liberia
3	Burkina Faso	20	Malawi
4	Burundi	21	Madagascar
5	Cameroon	22	Mali
6	Chad	23	Mozambique
7	Comoros	24	Namibia
8	Congo, Rep.	25	Nigeria
9	Cotd'Ivoire	26	Niger
10	Central African Republic	27	South Africa
11	Ethiopia	28	Sudan
12	Equatorial Guinea	29	Serra Leon
13	Gabon	30	Swaziland
14	Ghana	31	Uganda
15	Guinea	32	Tanzania
16	Guinea-Bissau	33	Zambia
17	Kenya	34	Zimbabwe