SPATIAL ECONOMETRICS ANALYSIS WITH IMPLICATION TO OKUN'S LAW AND PHILLIP'S CURVE IN NIGERIA.

BY

OKORO-UGOCHUKWU, NZUBECHUKWU AUGUSTINA

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A THESIS SUBMITTED TO THE SCHOOL OF POSTGRADUATE STUDIES, NASARAWA STATE UNIVERSITY KEFFI, IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF DOCTOR DEGREE OF PHILOSOPHY (Ph.D) IN STATISTICS.

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NIGERIA.

MARCH, 2022.

DECLARATION

I hereby declare that this thesis has been written by me and it is product of my research work. It has not been presented in any program for the award of Doctor of Philosophy (Ph.D). Also, all quotations and sources of information used are dully acknowledged by means of references.

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CERTIFICATION

This thesis, "Spatial Econometrics Analysis with Implication to Okun's law and Phillip's curve on the Nigerian Economy", meets the regulations governing the award of Doctor of Philosophy (Ph.D.) degree of the School of Postgraduate Studies, Nasarawa State University, Keffi, and it is approved by the under-listed signatories for its contribution to knowledge.

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DEDICATION

This thesis is dedicated to God Almighty. The thesis is also dedicated to My Husband. Mazi Okoro Ugochukwu, My Parents Late Mr Pius Ukwandu and Mrs Josephine, although my father did not live to see the actualization of the dream.

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To my family, Mr Okoro Ugochukwu (Husband)and our children, I am pleased with your abundant love, care and understanding which you showed me throughout the course of this study. I have no doubt that you have been blessed already by God. Thanks for your support.

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ABSTRACT

In recent times, spatial econometrics application is given reasonable attention as it deals with data of spatial type either in cross-sectional or panel form. This study examined application of Phillip's Curve and Okun's Law on the Nigerian Economy using 2017 - 2018 cross-sectional data of consumer price index (CPI) as inflation rate and unemployment rate data sourced from the National Bureau of Statistics (NBS), Nigeria for Phillip's curve and 2018 cross-sectional data of Gross Domestic product (GDP) and unemployment rate data sourced from the National Bureau of Statistics (NBS), Nigeria and from an economics website for Okun's Law. The Philips's curve states that inflation and unemployment rates have a stable and inverse relationship; Okun's law is an empirically observed relationship between unemployment rate and GDP of any country. Results from the Ordinary Least Squares (OLS) confirmed a negative relationship between inflation and unemployment in Nigeria though not significant while autocorrelation is present in the estimated model at 10% level of significance, however, results from the Ordinary Least Squares (OLS) reveal that there is positive relationship between unemployment rate and GDP in Nigeria though not significant while autocorrelation is present in the estimated model at 5% level of significance. For Phillip's curve, the Moran I statistic for spatial autocorrelation test is only significant at 10% while the Monte-Carlo simulation of Moran I statistic at 10,000 simulations revealed the presence of spatial autocorrelation at 1% level of significant while in Okun's law the Moran I statistic for spatial autocorrelation test is significant at 5% while the Monte-Carlo simulation of Moran I statistic at 10,000 simulations revealed the presence of spatial autocorrelation at 5% level of significant. The following spatial models namely: Spatial Lag Model (SLM), Spatial Error Model (SEM) and Spatial Autoregressive with Autoregressive Error Structure (SARAR) were applied in this study. The result from the spatial lag model shows a unit increase in unemployment leads to a decrease of 0.0011 of inflation rate in Nigeria. Lastly, a unit increase of unemployment in one state of Nigeria produces a total impact of reduction of 0.0014 in inflation rate. The findings support Phillip's Curve, but the relationship is not significant in the case of the Nigerian Economy. In addition, result from Spatial Lag Model shows a unit increase in GDP leads to an increase of 0.0497 with increase in Unemployment rate in Nigeria and a unit increase of GDP in one state of Nigeria produces a total impact of increment of 0.1306 in Unemployment rate. The findings contradict Okun's Law, but the relationship is not significant in the case of the Nigerian Economy.

Table of Contents

Cover Page i

Title Page ii

Declaration iii

Certification iv

Dedication v

Acknowledgements vi

Abstract vii

Table of Contents viii

List of Tables xi

List of Figures xii

CHAPTER ONE
INTRODUCTION

1.1 Background to the Study 1

1.2 Statement of the Study 5

1.3 Aim and Objectives of the Study 5

1.4 Significance of the Study 6

1.5 Scope of the Study 6

1.6 Definition of Operational Terms 6

CHAPTER TWO
LITERATURE REVIEW

2.1 Conceptual Framework 8

2.2 Empirical Review 8

2.2.1 Empirical Review on Spatial Econometrics 13

2.2.2 Empirical Review on Okun's Law 14

2.2.3 Empirical Review on Phillips Curve 22

CHAPTER THREE
RESEARCH METHODOLOGY

3.1 Research Design 30

3.2 Methods of Data Collection 30

3.3Technique for Data Analysis 30

3.4 Justification of Methods 30

3.5 The Classical Model with Spatially Lagged Non-Stochastic Regressors 34

3.6 The Spatial Error Model (SEM) 34

3.7 A Primer for Spatial Econometrics 35

3.8 The General SARAR(1,1) Model 36

3.9 Maximum Likelihood Estimator 38

3.10Interpretation of The Parameters in Spatial Econometric Models 39

3.11R Codes: Estimating Linear Spatial Models 42

CHAPTER FOUR
DATA PRESENTATION AND ANALYSIS

4.1 Data Presentation and Result on Okun's Law 43

4.2 Discussion of Result for Okun's Law 46

4.3 Data Presentation and Analysis of Philip's Curve 48

4.4 Discussion of Result on Philip's Curve 51

CHAPTER FIVE
SUMMARY, CONCLUSION AND RECOMMENDATION

5.1 Summary of findings for Okun's Law 53

5.2 Summary of findings for Phillip's curve 53

5.3 Conclusion 54

5.4 Recommendations 54

5.5 Contribution to Knowledge 54

5.6 Limitation of the study 55

5.7 Suggestion for further study 55

References 56

Appendix A 65

Appendix B

Appendix C

List of Tables

Table 4.1: Result on Okun's Law in Nigeria 43

Table 4.2:Result on Philip's Curve in Nigeria 49

List of Figures

Fig.1.1 Graph of Phillip curve: Inflation vs unemployment (scatter plot) – 1/2000 - 8/2014 12

Fig 2.1 Graph of rate of Inflation vs unemployment level 24

Fig 4.1 Scattered plot between GDP and unemployment in all the states in Nigeria between 2017-2018 45

Fig 4.2 Scattered plot between Inflation and Unemployment in all the states in Nigeria in 2017 – 2018 51

CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

Spatial econometrics has been seen to have a relatively short history in the scenario of the scientific thought. It was introduced was introduced only forty years ago during the general address delivered by Jean Paelinck to the annual meeting of the Dutch Statistical Association in May 1974 (Paelink & Klaassen, 1979; Arbia, 2014).

Spatial econometrics can also be viewed in a wide sense involving developments of models and statistical tools for the analysis of outwardness, spillovers, interactions etc., in various areas including economics, geography and regional science.

The term spatial econometrics is a subfield of econometrics that deals with spatial interaction effects among geographical units and locations where by units could be zip codes, cities. municipalities, regions, counties, states, jurisdictions, countries, and so forth depending on the nature of the research. The Spatial econometric models can also be used to explain the behavior of economic agents other than geographical units, such as individuals, firms, or governments. if they are related to each other through networks, but this type of research, although growing. is less common.

We have two major problems emerging in this estimation: first, the problem of endogeneity. as the response variable appears both on the left and right-hand side of the equation and then the secondproblem is the problem of identification that is if the number of parameters to be estimated exceeds the number of observations. Using spatial panel data models is the most obvious way of overcoming the problem of identification by exploiting the time replication to increase the number of available observations.

Spatial econometrics is of course a rapidly expanding topic with applications inso many diverse scientific fields that it is almost impossible to fully enumerate all the disciplines. Indeed, in recent years we can find applications on fields such as regional economics, criminology, public finance, industrial organization, political sciences, psychology, agricultural economics. health economics, demography, epidemiology, managerial economics, urban planning, education, land use, social sciences, economic development, innovation diffusion, environmental studies, history, labor, resources and energy economics, transportation, food security, real estate. marketing, and many others.

Given the well-known interest in the subject, this research aims to meet the growing demand by introducing basic spatial econometrics methodologies to a wide variety of researchers. It is specifically designed as a reference for applied researchers who want to have or receive a broad overview on the topic or the sturdy.

In this work, Spatial econometrics models such as Spatial lag model, Spatial error model and Spatial Auto-regressive with additional autoregressive error structure were applied to economic laws such as Okun's law and Phillip's curve on the Nigerian economy.

Okun's law is the relationship between an economy's unemployment rate and its Gross National product. It further says that a country's Gross domestic product must grow at about a 4% rate of one year to achieve a 1% reduction in the rate of unemployment.

Several authors have considered Okun's law on different economy. Some of the include: Anderton, Aranki, Bonthuis & Jarvis, (2014) examined the usefulness of Okun relation as a "rule of thumb" for predicting changes in unemployment as a result of changes in GDP output. The countries they considered revealed a negative relationship between unemployment and GDP.

Schnabel, (2002) estimated trend growth rates for a sample of industrial countries by applying Okun's law in first differences. The result revealed a negative relationship between unemployment rate and output growth.

On the other hand, Phillips curve describes the inverse relationship between unemployment and inflation, it also details the trade-off relationship and interdependency between the inflation rate and unemployment rate of a nation, simply put, decreased unemployment, (i.e., increased levels of employment) in an economy will correlate with higher rates of wage rises A.WPHILLIPS.

The study by Malinov and Sommers (1997) found that the Phillips curve is evident and stable in the short-run for many OECD countries, but they also found that the relationship for the United States deteriorated since 1970s.

However, Naghdi et al. (2011) tested the Phillips curve hypothesis for Iran and claim to have found a long-term inverse relationship between inflation and unemployment rate.

It may also impress you to know that the long-term relationship has been also noted by Tang and Lean (2007) whose investigation suggested that there is a trade-off between inflation and unemployment in Malaysia, both, in the shortand long-term.

However in the short-run, Kajuth (2012) found an economically significant trade-off between inflation and the unemployment gap for the US and an even more significant one for the Euro area.

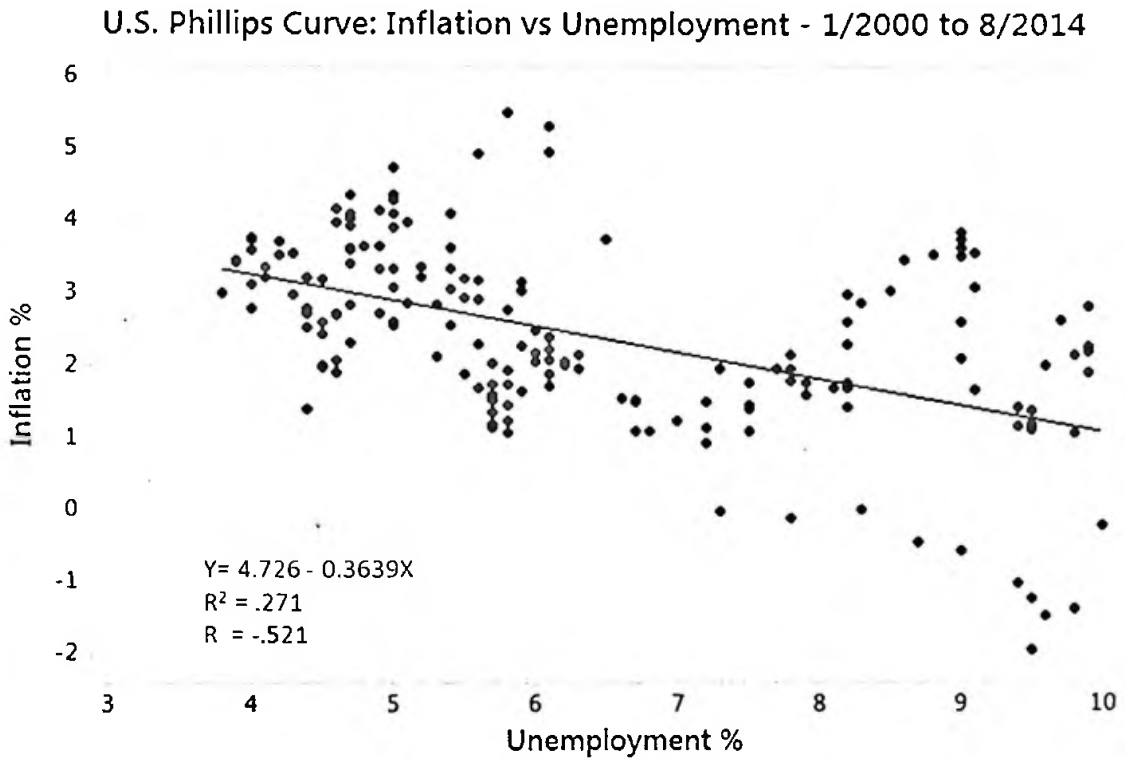
de Mendonc¸(2009) analyzes the adoption of inflation targeting in Brazil and finds that there is no unemployment-inflation trade-off even in the short run.

On the other hand, Baltagi et al. (2007) analyze the period 1980–2004 for West German wage curve and conclude that the wage equation is not a pure Phillip's curve, but it is a dynamic wage curve.

Granger and Jeon (2011) adopt a timevarying parameter linear model similar to Phillips' model and apply this to four different economies that are the US, the UK, Australia, and Turkey. They conclude that the basic relationship found by Phillips is still there in a nonlinear form but with

changing coefficients. According to them, the causation is one way and nonlinear, from unemployment to inflation but not in reverse direction.

Fig.1.1: Phillips curve plot.



Source Data: FRED Database
Inflation: CPI for All Urban Consumers

The above plot is a scattered plot of US Phillip's curve of Inflation vs Unemployment – 1/2000 to 8/2014.

It states that when there is a rise in the inflation rate due to the high economic growth, more jobs are available for the unemployed and therefore unemployment will fall. However, the existence of the Phillips curve in high-income countries has not received much scrutiny in the sense that countries with high income should have low unemployment rate, suggesting a high inflation. Besides, some of the high-income economy countries, the United States in 1970s for instance, failed to avert stagflation whereby high unemployment rate and inflation occurred at the same

time. This situation negates the Phillips curve. A wrong decision on policies can aggravate the economy.

1.2 Statement of the Study

There are two major problems emerging in this estimation: firstly, a problem of endogeneity. as the response variable appears both on the left and right-hand side of the equation, Endogenous variables can be present in various cases in econometrics like the case of errors in variables or the case of simultaneity(Greene, 2011) and secondly a problem of identification if the number of parameters to be estimated exceeds the number of observations. Using spatial cross-sectional or panel data models is the most obvious way of overcoming the problem of identification by exploiting the time replication to increase the number of available observations.

Also, Econometrics data collected with respect to geographical or spatial features tends to exhibit spatial autocorrelation when parameters are estimated only by Ordinary Least Square (OLS) method. To overcome this limitation from OLS, Spatial models such as Spatial Lag Model (SLM), Spatial Error Model (SEM) and Spatial Auto-regressive with additional Auto-regressive error structure (SARAR) were employed.

1.3 Aim and Objectives of the Study

1.3.1 Aim: The aim is study Spatial Econometrics with implication to Okun's in Nigeria and Phillips curve in Nigerian economy.

1.3.1 Objectives of the Study:

i. To fit Spatial Lag Model (SLM) to the Nigerian economy with application of Okun's Law and Phillip's curve.

ii. To fit Spatial Error Model (SEM) to the Nigerian economy with application of Okun's Law and Phillip's curve.

iii. To fit Spatial Auto-regressive with additional Auto-regressive error structure to the Nigerian economy with application of Okun's Law and Phillip's curve.

.1.4 Significance of the Study

Researchers such as Econometricians, will obtain more robust result by applying Spatial Model against Ordinary least squares and this will lead to perfect recommendations and conclusions on their research work. This work will also form basis for post graduate students for further research.

This research work will be useful for planning and development agencies for short term, long term and portfolio investors and other relevant stakeholders.

This research work will also help policy makers during their decision making.

1.5 Scope of the Study

The research covers Spatial Econometrics with implication to Okun's Law and Phillip's Curve in Nigeria using cross sectional data set from 2017 to 2018

1.6 Definition of Operational Terms

1. Phillip's Curve:

This is showing the relationship between inflation and unemployment. Inflation and unemployment are inversely related to each other.

2. Okun's Law:

Okun's law is the relationship between an economy's unemployment rate and it's Gross National Product (GNP).

3. Cross-Sectional Data:

Cross sectional data or a cross section of a sturdy population. In Statistics and econometrics, it is a type of data collected by observing many subjects such as individual, firms, countries, or region at the one point or period

4. Endogeneity:

In Econometrics, endogeneity broadly refers to situations in which an explanatory variable is correlated the error term. This may arise due to the omission of explanatory variable in a regression which result in error terms being correlated with the explanatory variable

5. Autocorrelation:

It's a mathematical representation of the degree of similarity between a given time series and a lagged version of itself over successive time intervals.

6. Spatial Data:

Any type of data that directly or indirectly reference a specific geographical area or location.

7. Spatial Autocorrelation:

This is the presence of systematic spatial variation in a variable

8. Identification in Econometrics:

This is a problem which tell whether structural parameters can be obtained or not from reduced from parameters.

9. Consumer Price Index (CPI):

Is a measure of the average change overtime in the prices paid by urban consumers for a market basket of consumer goods and services.

CHAPTER TWO

LITERATURE REVIEW

2.1 Conceptual framework

The study would have some literature reviewed on the research studies that would enable us to understand other work done on this same research by other researchers. Challenges and issues of the combination of unemployment and inflation, GDP and unemployment is what every country try to avoid. Truly, these two indicators are majorly used to measure the performance of any country in this world. Recall that Okun's law is concerned about the country's Gross National product (GNP) and unemployment while Phillip's curve has an inverse relationship between inflation and unemployment. We therefore have review on the following.

Spatial econometrics can be defined in two ways, a narrow and in a broader sense. In a narrow sense it refers to methods and techniques for the analysis of regression models using data observed within discrete portions of space such as countries or regions. In a broader sense it is inclusive of the models and theoretical instruments of spatial statistics and spatial data analysis to analyze various economic effects such as externalities, interactions, spatial concentration, and many others.

Spatial econometrics is a branch of econometrics that began to emerge in the 1970s and 1980s. The spatial correlation study in the economic field can be dated back to Cliff and Ord (1973), but until the late 1970s, Paelinck and Klaassen (1979) coined the term spatial econometrics for the first time and outlined the five main characteristics of spatial econometrics: (1) the role of spatial interdependence in spatial models; (2) the asymmetry in spatial relations; (3) the importance of explanatory factors located in other spaces; (4) the differentiation between ex-post and ex-ante interaction; and (5) the explicit modeling of space (Paelinck and Klaassen, 1979).

On the basis of Paelinck and Klaassen (1979), Anselin (1988) provides a new definition and richer contents on spatial econometrics and defines spatial econometrics as "the collection of techniques that deal with the peculiarities caused by space in the statistical analysis of regional science models." According to Anselin, "Spatial econometrics is a subfield of econometrics that deals with spatial interaction (spatial autocorrelation) and spatial structure (spatial heterogeneity) in regression models for cross-sectional and panel data" (Baltagi 2001).

In spatial interaction models, the strength of knowledge spillovers is assessed by introducing spatial distance as an explanatory variable of the intensity of the patent citation flows between regions (LeSage et al., 2007; Fischer & Griffith, 2008; Bergman & Usai, 2009).

What distinguishes spatial econometrics from traditional econometrics? Two problems arise when sample data has a locational component:

1. Spatial dependence between the observations and
2. Spatial heterogeneity in the relationships we are modeling.

Traditional econometrics has largely ignored these two issues, perhaps because they violate the Gauss-Markov assumptions used in regression modeling. With regard to spatial dependence between the observations,recall that GaussMarkov assumes the explanatory variables are fixed in repeated sampling.

Anselin and Griffith (1988) also provide examples and show that traditional specification tests are plagued by the presence of spatial autocorrelation, so that we should not rely on these tests in the presence of significant spatial autocorrelation.

Anselin (1988) provides a complete treatment of many facets of spatial econometrics which this text draws upon. In addition to introducing ideas set forth in Anselin (1988), this presentation

includes some more recent approaches based on Bayesian methods applied to spatial econometric models.

Casetti (1972, 1992) introduced our first approach that involves a method he labels "spatial expansion". The model where y denotes an nx1 dependent variable vector associated with spatial observations and X is an n x nk matrix consisting of terms xi representing kx1 explanatory variable vectors.

The locational information is recorded in the matrix Z which has elements

Zxi, Zyi, i = 1,...,n, that represent latitude and longitude coordinates of each observation.

Another approach to modeling variation over space is based on locally weighted regressions to produce estimates for every point in space by using a sub-sample of data information from nearby observations. McMillen (1996) and Brundson, Fotheringham and Charlton (1996) introduce this type of approach. It has been labeled "geographically weighted regression", (GWR) by Brundson, Fotheringham and Charlton (1996).

A first distinction is between continuous spatial data and data observed on a discrete space. Continuous spatial data are very common in many scientific disciplines (such as physics and environmental sciences) but are still not currently considered in the spatial econometrics' literature. Discrete spatial data can take the form of points, lines, and polygons. Point data refer to the position of the single economic agent observed at an individual level. Lines in space take the form of interactions between two spatial locations such as flows of goods, individuals and information.

Spatial econometrics is still a relatively young discipline in the wider scenario of the scientific thought. Indeed, the term "spatial econometrics" was introduced for the first time 40 years ago by the Belgian economist Jean Paelinck (universally recognized as the father of the discipline) in the general address he delivered at the annual meeting of the Dutch Statistical Association in May 1974 (Paelinck and Klaassen, 1979).

In a narrow sense it refers to methods and techniques for the analysis of regression models using data observed within discrete portions of space. In a broader sense it is inclusive of the models and theoretical instruments of spatial statistics and spatial data analysis to analyze various economic effects such as externalities, interactions, spatial concentration, and many others. Indeed, in the already quoted founding book by Paelinckand Klaassen (1979) the authors indicate four paradigmatic models that constitute the backbone of the discipline. The first model is a *spatial income-generating model* revised to account for the presence of spatial spillovers.

The model is basically an asymmetric simultaneous spatial autoregressive model (Whittle, 1954), that, for three regions, takes the form:

$$y_1 = \alpha^{au} y_2 + \beta^{au} y_3$$

$$y_2 = \alpha^{ua} y_1 + \beta^{uu} y_3$$

$$y_3 = \alpha^{ua} y_1 + \beta^{uu} y_2$$

With y_i indicating the income of region i, $\alpha^{au} \neq \alpha^{ua}$,$\beta^{au} \neq \beta^{ua}$and the superscripts a and u indicating, respectively, an agricultural and an urban area. The second paradigmatic model

described by Paelinck and Klaassen (1979) is the *attraction model*, an example of sectorial Weberian–Loeschian location analysis (Weber, 1909; Loesch, 1940)

It's established that Okun (1962) built three versions of models to establish the interaction between unemployment and output. These include: the difference model, the gap model and the dynamic model. The difference model shows the effect of movements in output on change in unemployment rate. It reflects the relationship between unemployment and economic growth.

The model is specified as:

$$U_t - U_{t-1} = \sigma + \beta(Y_t - Y_{t-1}) + \mu_t \qquad 2.1$$

U_t is unemployment rate at current period; U_{t-1} is unemployment rate at previous period; Y_t is output at current period; Y_{t-1} is output at previous period; $U_t - U_{t-1}$ is change in unemployment rate; $Y_t - Y_{t-1}$ is change in output; β is Okun's coefficient or estimate of change in output: σ is intercept; μ is error term.

Equation (1) in a simpler form becomes:

$$\Delta U = \sigma + \beta \Delta Y + \mu \qquad 2.2$$

ΔU is change in unemployment; ΔY is change in output.

The gap model shows how the difference between potential output and actual output affects current unemployment rate. Okun (1962) used the gap model to explain the output the economy can produce when there is full employment and no inflationary pressure. The model assumes that the economy attains full employment when unemployment is 4% (Arshad, 2011). The gap model is specified as:

$$U = \sigma + \beta(Y_t^* - Y_{t-1}) + \mu_t \quad 2.3$$

U_t is unemployment rate at current period; Y_t^* is potential output; Y_t is actual output: $Y_t^* - Y_t$ is output gap.

The dynamic model assumes that current rate of unemployment is determined by current output. previous output and previous changes in unemployment.

Knotek (2007) opines that the model is distinctive because it does not reveal only the relationship between changes in unemployment and output growth but also how past unemployment level affects present unemployment level. The model is specified as:

$$U_t = \sigma + \beta_1 Y_t + \beta_2 Y_{t-1} + \alpha U_{t-1} + \mu_t \quad 2.4$$

U_t is unemployment rate at current period; Y_t is output at current period;

Y_{t-1} is output at previous period; U_{t-1} is unemployment rate at previous period; $\beta 1$ and $\beta 2$ are Okun's coefficients.

2.2 Empirical Review On Spatial Econometric

According to Anselin, "Spatial econometrics is a subfield of econometrics that deals with spatial interaction (spatial autocorrelation) and spatial structure (spatial heterogeneity) in regression models for cross-sectional and panel data" (Baltagi 2001).

This takes the form of a system of equations to explain the flows of import, export, and transportation costs between regions. The third model was termed the *threshold* effect, a mechanism that relates the birth–growth–death of new establishments to regional location

profiles that, in turn, are indicative of the expected relative profitability of production in each region.

Finally, the fourth model is a space-integrating shopping model that aims at explaining the flows of customers towards a set of spatially located shopping centers.

In the same book Paelinck and Klaassen (1979) identified five fundamental characteristics of spatial econometrics, namely:

i. The role of interdependence in spatial models;

ii. The asymmetry of spatial relations;

iii. The importance of explanatory factors located in other spaces;

iv. The differentiation between ex-post and ex-ante interaction;

v. The explicit modeling of space. Many of these characteristics have been rather overlooked in the narrower interpretation of spatial econometrics.

2.3 Empirical Review on Okun's Law

In economics, Okun's law is an empirically observed relationship between unemployment and losses in a country's production. Arthur Okun was a Yale professor and economist who studied the relationship between unemployment and production. He first published his research on the topic in the 1960s, and his findings were established as Okun's law. It provides a general notion construing that when unemployment falls, the production of a country will increase. This measure can be used for estimating both GNP and GDP.

The "gap version" states that for every 1% increase in the unemployment rate, a country's GDP will be roughly an additional 2% lower than its potential GDP.Okun's law states that for every 1% increase in the employment rate, gross domestic product increases 3%.

Several authors have considered Okun's law on different economy. Some of the include: Anderton, Aranki, Bonthuis & Jarvis, (2014) examined the usefulness of okun relation as a "rule of thumb" for predicting changes in unemployment as a result of changes in GDP output. The countries they considered revealed a negative relationship between unemployment and GDP.

Schnabel, (2002) estimated trend growth rates for a sample of industrial countries by applying Okun's law in first differences. The result revealed a negative relationship between unemployment rate and output growth.

Owyang & Sekhposyan, (2012) reconsidered the evidence on instability in Okun's law, in particular, they examined whether the Great recession has contributed to the breakdown of the empirical relationship stated in the Okun's law. Their result revealed negative relationship between unemployment rate and real GDP growth.

Ball, Leigh & Loungani, (2012) examined how well Okun's law fits short-run unemployment movements in the united states since 1948 and in twenty advanced economics since 1980. They found out that Okun's law is a strong and stable relationship in most countries, one that did not change substantially during the Great Recession.

Higgins, (2011)examined GDP growth, the unemployment rates and Okun's law since June 2009 and concluded that unemployment rate decline by 0.4% while real GDP growth increased by 2.4%.

Ball, Jalles and Loungani (2014) found that real GDP growth forecasts and changes in unemployment are inversely related in 9 developed countries.

Okun's law can also pertain to how a rise in unemployment affects gross domestic product (GDP), where a percentage increase in unemployment causes a 2% fall in GDP.

Rubcova (2010) estimates Okun's coefficient for Baltic States using cointegration and error correction model framework. The study also utilizes Hodrick-Prescott filter which allows the trend to change smoothly and gradually in the course of real business cycles analysis. The results of the study do not provide evidence in support of strong relationship between unemployment and output. The study, therefore, suggests data reliability issues and labour market features as reasons for such results.The percentage increase by which GNP changes when unemployment falls by 1% is the Okun coefficient.

The relationship between unemployment and GNP or GDP varies by country. In the United States, the Okun coefficient estimates that when unemployment falls by 1%, GNP will rise by 4% and GDP will rise by 3%. When unemployment rises by 1%, then GNP is expected to fall by 4% and GDP is expected to fall by 3%.

Economists broadly support Okun's law, but it's considered to be inaccurate. This comes as numerous variables are involved with changes in GNP and GDP. Economists support an inverse relationship between unemployment and production, believing that when unemployment rises, GNP and GDP will simultaneously fall, and when unemployment declines, GNP and GDP are expected to increase, but the exact amount varies.

Further studies on the relationship of unemployment to production include a broader set of labor market variables to analyze the effects of the labor market on GNP and GDP. More detailed labor market variables include the level of the total labor market, hours worked by employed workers and productivity levels for workers. Under further analysis, economists have found the change in production for every 1% change in unemployment to vary with more volatility than Okun's law sets forth.

Okun's law was propounded in 1962 from a study which discovered an inverse relationship between unemployment level and economic growth of the US between 1947Q2 and 1961Q1 and later studies such as Weber (1995); Knotek (2007); Kitov (2011); Ball, Leigh and Loungani (2013); Ekner (2013) and Ball, Jalles and Loungani (2014) provide similar evidence for the US economy.

However, Daly and Hobijn (2010) and Gordon (2011) showed that Okun's law is not a norm in US. This implies that Okun's law has generated controversy in the US economy. Similarly, findings not related to US have produced mixed results. Sadiku, Ibraimi and Sadiku (2015), utilising quarterly data from 2000 - 2010, observed the relationship between economic growth and unemployment rate in Macedonia. The findings suggest that Okun's law is not tenable.

For Nigeria, Sodipe and Ogunrinola (2011) explored the statistical link between employment rate and Nigerian economic growth using ordinary least squares (OLS) method. The empirical results show that the relatively low influence of GDP growth to promote employment is responsible for the high level of unemployment and that Okun's law does not hold.

Arewa and Nwakanma (2012) adopted vector autoregressive (VAR) approach to estimate the relationship between output and unemployment in Nigeria from 1981 - 2011. The study found that Okun's law does not fit to the Nigerian economy.

Babalola, Saka and Adenuga (2013) investigated the authenticity of Okun's law in Nigeria from 1980 - 2010. Employing Granger causality test and Error-correction model, the findings indicated that causality flow in a Bidirectional manner from unemployment to real output growth and the coefficient of Okun is also not negative. The study suggests that unemployment rate fails to respond to economic output growth in a manner that is consistent with Okun's law.

Abraham (2014) examined the effect of output on unemployment rate in Nigeria between 1985 and 2013. Using autoregressive distributed lag (ARDL) bounds-test; it was then discovered that output (GDP) variations have no significant impact on unemployment. The study concluded that Okun's law is not validated in Nigeria. Economy.

Also, Akeju and Olanipekun (2014) employing the error-correction modelling approach, did not validate Okun's law in Nigeria.

Schnabel, (2002) estimated trend growth rates for a sample of industrial countries by applying Okun's law in first differences. The result revealed a negative relationship between unemployment rate and output growth.

Barreto & Houland, (1993) considered two Okun's law relationships between output and unemployment and applied same to the Japan economy. The results revealed a negative relationship between unemployment rates and output.

According to Geldenhuys and Marinkov (2007) on Robust estimations of Okun's coefficient for South Africa's economy found out that unemployment rate is inversely proportional (related) to

economic growth output of South African economy in the period of 1970 to 2005 and that there exists evidence of asymmetry in the Okun's relationship.

But on the other hand,Moroke, Leballo and Mello (2014) estimated therelationship between unemployment rate and economic growth of South Africa from 1990Q1 - 2013Q4 showing that the study showed that Okun's coefficient negates the expected sign; thus, affirming that Okun's law is irrelevant in South Africa.

Akram, Hussain and Raza (2014), applied ordinary least square method, and found out that Okun's law does not exist in Pakistan.

The study of Central Bank of Malta (2013) found that GDP growth above 1.5% - 2.0% reduces the rate of unemployment. However, the influence of GDP growth on unemployment is weak when compared with other European Union (EU) countries.

In Spain, Loría and Salas (2014) using the quadratic version of the first difference of Okun's law model for the period between 1995Q1 and 2012Q2. The study disagreed that Okun's law is not stable over time and observed that 7.38% growth rate reduces changes in unemployment.

Kargi (2014), in a study of 23 Organization for Economic and Cooperation Development (OECD) countries, found that unemployment and growth do not move in the same direction.

Similarly, Dixon, Lim, and van Ours (2016) found that increase in economic growth would reduce unemployment rate as well as have a distributional effect of reducing unemployment among youths in 20 OECD countries.

Noor, Nor and Ghani (2007)investigated howeconomic growth interacts with unemployment in Malaysia from the year 1970 - 2010. The regression results obtained from the study indicates the responsiveness of unemployment to growth behaviour is in line with Okun's law.

Elshamy (2013) evaluated the dynamic relationship between unemployment rate and economic growth output in Egypt from 1970 and 2010. It was discovered that Okun's coefficient is statistically significant in both the short run and long run.

Dritsaki and Dritsaki (2009) estimated Okun's coefficient between 1961 and 2002 for 4 Mediterranean countries of the EU consisting of Italy, Spain, Portugal and Greece between 1961 and 2002 and found the coefficient to be –0.024, –0.017, –0.016 and –0.007 respectively.

Kitov (2011) investigated Okun's law for six developed countries comprising United States, Spain, United Kingdom, Australia, Canada and France. Using real GDP per capita in place of overall GDP, Okun's law exhibits an astounding predictive power in all the countries. The study showed that the high unemployment rates in these countries would not be reduce if their growth rate does not exceed 2% per annum.

Christopolous (2004) investigated the Okun's law in Greece on regional basis and found that the law is evident in 6 out of the 13 regions reviewed.
Similarly, Binet and Francois (2013) found Okun's law to be valid in 14 out of 22 regions in France.

Other studies have followed investigating empirically the relationship between output and unemployment (Lee, 2000; Viren, 2001; Silverstone and Harris, 2001; Sogner and Stiassny, 2002). These studies mostly revealed the validity of the relation between output and unemployment rate. However, the estimates of Okun's coefficient vary substantially across countries and regions.
Moosa, (2008) studied the validity of Okun's law in four Arab countries: Algeria, Egypt, Moroco and Tunisia. He found that output growth does not translate into employment gains for the four countries, which means that Okun's coefficient turn out to be statistically insignificant. Knotek (2007), estimated Okun's law using three versions, the difference, gap and dynamic

version, in which he calculated effects on unemployment rate by current output, past output level, past unemployment rate and analyzed the slowdown in economy coincided with increase in unemployment rate is not always the case in both short and long run.

Mitchell and Pearce (2010) also have found that unemployment rate and GDP growth move in opposite direction but the change in unemployment rate causes less influenced in GDP growth as compared to Okun's coefficient benchmark.

Christopoulos (2004) also estimated Okun's law at regional level in Greece by applying unit root tests and cointegration tests on panel data and found that results are consistent in six out of thirteen examined regions. Sogner (2001) estimated Okun's law on Austrian economy by using quarterly data of unemployment rate and GDP growth. The Okun's coefficient found to be 4.16 which are almost 2 to 3 percent initially. Neely (2010) noted that industrialized countries with less regulated labor markets tend to have smaller Okun's coefficients. This is because unemployment is more sensitive to changes in output since it is easier to lay off workers. He adds, "The Okun's coefficient can change over time because the relationship of unemployment to output growth depends on laws, technology, preferences, social customs, and demographics".

Prachowny (1993) estimated Okun's law using its gap version and then he calculated non-accelerating inflation rate of unemployment (NAIRU) and output gap and verifies negative association between variables involved.

Freeman (2001) tested Okun's law for ten industrial countries (US, UK, Japan, Canada, Germany, Italy, France, Netherlands, Sweden, Australia) including new developments with trend decomposition and found that Okun's coefficient which was originally three points is now only less than two point's growth in GDP for every one percent change in unemployment rate for selected countries.

Irfan et al. (2010) checked the validity of Okun's law in some Asian countries using annual data from 1980-2006. They found that Okun's Law is not applicable in some of Asian developing countries.

Meidani and Zabihi (2011) examine the dynamic effect of unemployment rate on per capita real GDP in Iran over the period 1971 and 2006. Using an Auto-Regressive Distributed Lag (ARDL),

the study finds that the unemployment rate has a significant and negative effect on per capita real GDP in the long-run and short-run periods.

Lal et al. (2010) test the validity of Okun's law in some selected Asian countries using time series annual data during the period 1980-2006. The study employs Engle-Granger (1987) cointegration technique to establish the long-run relationship between the variables of interest and error correction mechanism for short-run dynamics. After the empirical analysis, the results of the study indicate non-applicability of Okun's law in some Asian countries.

2.4 Empirical Review on Phillips Curve

The Phillips curve details the trade-off relationship and interdependency between the inflation rate and unemployment rate of a nation. It states that a rise in the inflation rate due to the high economic growth, more jobs are available and therefore unemployment will fall.

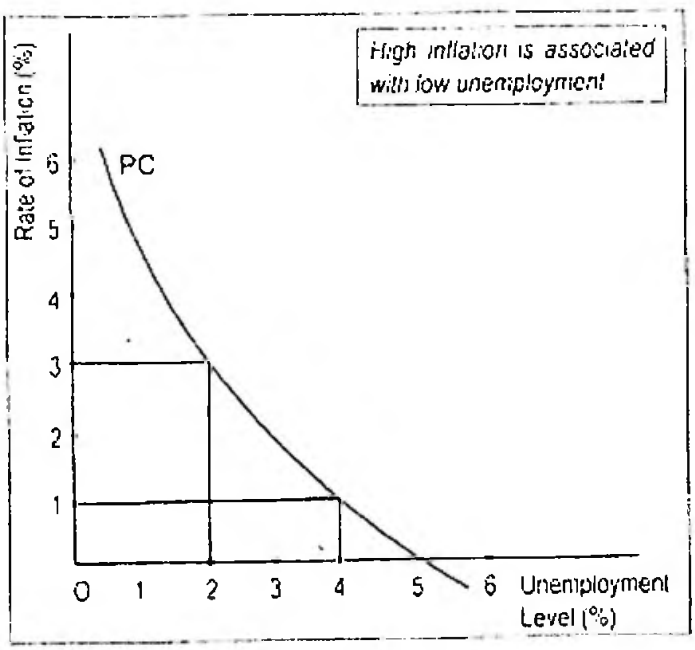


Fig. 2.1 Phillips Curve

The Phillips curve, drawn in Fig. 2.1, shows that as the unemployment level increases, the rate of inflation falls.

Thus, there exist a tradeoff between inflation and unemployment, the higher the inflation rate, the lower the unemployment rate.

However, the existence of the Phillips curve in high-income countries has not received much scrutiny. Countries with high income should have low unemployment rate, suggesting a high inflation. Besides, some high-income economy countries, the United States in 1970s for instance, failed to avert stagflation whereby high unemployment rate and inflation occurred at the same time. This situation negates the Phillips curve. A wrong decision on policies can aggravate the economy.

Furuoka and Munir (2012) in Malaysia have investigated the existence of the Phillips curve in various countries. Their findings were consistent, that is, the Phillips curve exists in their respective countries. Meanwhile, a limited number of studies explored this existence in high-income countries, such as the United States, and their findings confirmed the existence of the Phillip curve. However, the study focused only on one country and did not include other high-income countries. Countries with high incomes should have low unemployment rate, suggesting a high inflation rate. However, some high-income countries, the United States in 1970s for example, could not avert stagflation, thus high unemployment rate and inflation occurred in tandem.

Catik et al. (2011) found no evidence of a longterm relationship for Turkey, but by including the varianceand skew of the relative price changes, the error correction model implies a plausible short-term relationship.

Conversely, Niskanen (2002) and Reichel (2004) argue that the concept of the Phillips curve should indeed be buried and that as a policy guideline it is totally useless.

Niskanen (2002) goes even further and claims that the relationship between inflation and unemployment is positive in the long-term; that is, inflation creates unemployment if the inflation rate is lagged one year (based on the US data).

This is confirmed by the study of Haug and King (2014) who estimated the longrun vertical Phillips curve in the US using a band-pass filter approach. They found strong evidence that a positive relationship exists in which inflation leads to unemployment in 3–3.5 years, occurring in cycles that last from 8 - 25 or 50 years.

Furuoka and Munir explored the connection between unemployment rate and inflation rate in Malaysia. Malaysia was chosen as it is a developing country and many previous studies have focused on developed countries. The data from 1975 - 2004 were analyzed using the Johansen co-integration and error correction model tests. The results showed that there is a connection running from the unemployment rate to inflation rate in both short and long run. Therefore, these findings confirmed the existence of the Phillips curve in Malaysia.

Shaari et al. (2017) also examined the same connection in the same country. The study analysed the data from 1982 - 2010 using the Johansen c-integration and Granger causality tests. The finding revealed the existence of a negative connection between inflation and unemployment.

Schreiber and Wolters (2015) examined the existence of a connection between unemployment and inflation in Germany for the period 1977:2-2002:3. The study employed vector auto regression model and vector error correction model and the findings showed that there is a negative connection between inflation and unemployment in the long run.

Resurreccion *et al* (2016) extended the previous study by examining the connection between unemployment and inflation and economic growth within 1980-2009 but the study was done in Phillippines. The analysis was based on the ordinary least square test was employed and the findings showed that an increase in the inflation rate or economic growth can cause the unemployment rate to decrease. This inverse connection corresponded with the Phillips curve.

Karahan et al. (2013) examined the connection between unemployment and inflation in Turkey for the monthly data from 2006 - 2011. The Autoregressive Distributed Lag (ARDL) Bounds test was conducted and the findings showed that unemployment negatively affects inflation in the short run but there is no causal connection in the long run.

Ismael and Sadeq *et al* (2010) explored the connection between unemployment and inflation in Palestine for the quarterly data from 1996:2 - 2015:3. The study conducted the co-integration and Granger-causality tests and the findings revealed that inflation can affect unemployment negatively in the long run but positively in the short run.

Haug and King (2011) also investigated the long-run connection between inflation and unemployment in the United States for the period 1952 - 2010. The band-pass filter approach was used, and the findings however showed a positive connection between inflation and unemployment. Therefore, a rise in inflation rate can result in higher unemployment rate. Several studies examined the connection between inflation and unemployment in numerous countries and the existence of the Phillips curve can be confirmed.

Katria et al. (2011) selected 8 SAARC countries including Afghanistan, Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan, and Sri Lanka, and 6 expected countries of SAARC, namely, Republic of China, Russia, Indonesia, Iran, Myanmar, and South Africa to analyze the connection between inflation and unemployment for the same period of 1980-2010. The analysis was based on the multiple regression and the results indicated that there is a negative connection between inflation and unemployment rate in the SAARC Countries. Therefore, this finding is like the Phillips curve.

Islam *et al* (2003) examined Phillips hypothesis for USA data from 1950 until 1999 and found a weak long-run cointegrating relationship between unemployment and inflation.

Reichel (2004) applied cointegration methodology on Phillips hypothesis for the industrialised economies and found trade-off between inflation and unemployment only for USA and Japan.

Furuoka (2007) established the long-run and causal relationship between unemployment rate and inflation rate in Malaysia during the period of 1975–2004. Finally, Islam et al. (2011) examined the Phillips hypothesis for North Cyprus. The estimates point to the existence of Phillips curve both in the long and the short run.

Alogoskoufis and Phillippopoulos (1991) examined a 'rational partisan model' of inflation and unemployment for Greece which exhibit a high inflation rate in the last two decades for the examined period, attributing this situation in the failure of political parties to stabilise the prices, while unemployment seems independent from inflation rate.

Llaudes (2005) examines the short and long run relationship between unemployment and inflation for OECD countries including Greece.

As Ezeaku and Ugwuebe (2016) narrated it, the Phillips curve identifies thatdecrease in unemployment rate (increased in employment rate) moves in reverse order with increases in the rate of inflation. That is to say that a lower rate of inflation will bring about an increase in the level of unemployment. The above scenario which is a likely outcome will most likely operate only in the short-run, but at the long run other policies targeted at inflation may not guarantee such outcome.

Ezeaku and Ugwuebe (2016) in a related study, the responsiveness of unemployment to inflation in Nigeria made use of data between 1989s-2014. They adopted the Error Correlation Model (ECM) and the Johansen technique in their study. Their findings reveal that inflation has negative impact on unemployment while money supply and exchange rate were found to positively influenced unemployment in Nigeria. They conclude that despite the existence of long-run association between unemployment and inflation, there exists a divergence along the equilibrium part but such divergence is corrected anomaly at 65% speed of adjustment.

In similar scenario, a study on the relationship between unemployment and inflation in the US economy in Ezeaku and Ugwuebe (2016), who empirically demonstrated that there exists an inverse relationship between the variables of unemployment and inflation. That is when unemployment rate increases, inflation will take a downward trend, but when unemployment rate decreases, inflation will invariably increase. Such scenario entails a trade-off between the two variables and this becomes an issue of great concern to policy makers as either to accept higher rate of inflation will lower rate of unemployment or vice-versa.

In a different case, employees would predict inflation and an increase in wages would be possible. In such a case there would be high unemployment and high inflation rate known as the 'Lucas critique' (Dritsaki and Dritsaki, 2012).

Orji *et al.* (2015) noted that the Phillips curve hypothesis enjoyed some successes in its early stage as it became a popular macroeconomic yardstick that enjoyed greater acceptability and greater influence on government policies of the 1960s. In the words of Blanchard and Illing (2009), the Phillips curve influence and great regard for it as an instrument for policy making, the governments believe that they can either achieve low rate of unemployment amidst higher rate of inflation or alternatively tolerate higher unemployment rate amidst lower rate of inflation (price stability).

According to Orji *et al.* (2015), the discovery of the new relationship gave credence to the concept of modified Phillips curve and such is still valid, visible and applicable in many developed and developing economies the world over.

Umoru and Anyiwe (2013) in their study of the dynamics of inflation and unemployment in Nigeria using a Vector Error Correlation Model over a period of 27 years discovered the existence of stagflation in Nigeria over the studied period. They discovered that Nigerian

economy is battling with a shocking rate of inflation alongside a severe recession as the unemployment rate had risen astronomically. They conclude that the Nigerian economy is at the cross-road.

Kogid *et al.* (2013) while studying inflation-unemployment trade-off relationship in Malaysia using three robust econometrics methods ofAutoregressie Distributed Lag(ARDL) bonds testing technique, ECM based ARDL and Toda-Yamanoto (1995) techniques for the period 1975 – 2007. Their empirical result demonstrates that a longrun cointegration relationship exist between inflation and unemployment and a unidirectional causal relationship running from inflation to unemployment. They conclude that there is an evidence of inflation-unemployment trade-off relationship in Malaysia.

Odo *et al.* (2017) conducted a similar study titled understanding the relationship between unemployment and inflation in Nigeria between 1980 – 2015. They modeled unemployment as a function of inflation and adopted causality test, VECM and Johansen cointegration tests in their analysis. Their findings indicate that inflation had a significant impact on unemployment in Nigeria both in the short and long-run. They maintain that increases in government expenditure reduce unemployment and such government spending creates employment to the extent that inflation remains within the single digit ambit.

Iyeh and Edame (2017) in a similar investigation on price expectations and the Phillips curve hypothesis in the Nigerian economy made use of Persimonous Error Correction Model and Johansen method of cointegration. Their result revealed the prevalence of a direct (positive) relationship between inflation and unemployment in Nigeria and thus invalidates the Phillips curve hypothesis of an inverse (negative) relationship.

Saed and Salim (2017) undertook a study on inflation and unemployment in Nigeria using an ARDL model approach. They made use of annual time series data of 1977 to 2011 in their analysis. The result of the cointegration result indicates that a long-run relationship exists between the variables of inflation and unemployment in Nigeria. Their finding supports the applicability of Phillips curve hypothesis in Nigeria and as such contradicts the popular idea of the co-existence of unemployment and inflation in the country.

Edeme (2018) in his study, providing an empirical insight into Nigeria's Non-Accelerating Inflation Rate of Unemployment (NAIRU) made use of annual time series data between 1972 – 2015 obtained from the statistical bulletin of CBN. The Ordinary Least Square (OLS) method was adopted to ascertain if Phillips curve postulate exists in Nigeria both in the short-run and long-run. He equally estimated the non-accelerating inflation rate of unemployment in Nigeria. The emanating evidence from the empirical analysis established the existence of a negative but insignificant relationship between inflation and unemployment both in the short-run and long-run in Nigeria.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Research Design

This study used Cross-sectional dataset with the spatial dataset to examine Okun's Law and Phillip's curve in Nigeria. All analysis are done in R.

3.2 Methods of Data Collection

The study, used data from the National Bureau of Statistics Bulletin (NBS) 2017 - 2018 and from https://stateofstates.kingmakers.com.ng

3.3 Technique for Data Analysis

Spatial models such as Spatial Lag Model, Spatial Error Model and Spatial Autoregressive with additional Auto-regressive error structure were employed.

3.4 Justification of Methods

The following models such as Spatial Lag Model, Spatial Error Model and Spatial Autoregressive with additional Auto-regressive error structure are employed to account for spatial auto-correlation error that is inherent in cross-sectional data.

3.4.1 Spatial Linear Regression Models

3.4.2 Generalities

Here, there are different specifications of linear spatial econometric models that would be in the hypothesis of no spatial autocorrelation in the disturbances is disturbed. The overall form is to consider the violation of the ideal conditions for the applicability of OLS is given by the equations:

$$y = \lambda Wu + X\beta(1) + WX\beta(2) + u \qquad |\lambda| < 1 \qquad (3.1)$$

$$v = \rho Wu + \varepsilon \qquad |\rho| < 1 \qquad (3.2)$$

with X a matrix of non-stochastic regressors, W is the weight matrix exogenously given, $e \mid X \approx i.i.d.N(0,\delta_{\varepsilon n}^2 l_n)$ and $\beta_{(1)}$, $\beta_{(2)}$, λ *and* ρparameters are to be estimated. The restrictions on the parameters l and r hold if W is row-standardized.

Equation 3.1 considers the spatially lagged variable of the dependent variable y as one of the regressors and may also contain spatially lagged variables of some or all the exogenous variables (the term WX). The second equation considers a spatial model for the stochastic disturbances. In principle, there is no need that the three weight matrices in Equations (3.1) and (3.2) are the same, although in practical cases it is difficult to justify a different choice.

Equation (3.1) can also be written as:

$$y = \lambda W\gamma + Z\beta + v \qquad |\lambda| < 1 \qquad (3.3)$$

having defined the matrix of all regressors, current and spatially lagged, as $Z = [X,WX]$ and the vector of regression parameters as $b = [b\ (1),b\ (2)]$

This model was termed SARAR(1,1) (acronym for Spatial AutoRegressive with additional AutoRegressive error structure) by Kelejian and Prucha (1998) and encompasses several spatial econometric models. In particular we have five remarkable cases:

i. $b = 0$ and either l or $r = 0$, known as the pure spatial autoregressive model

ii. $\lambda = \rho = 0$, known as the Lagged independent variable model

iii. $\lambda = 0, \rho \neq 0$ known as Spatial Lag Model (SLM)

iv. $\lambda \neq 0, \rho = 0$ known as Spatial Error Model (SEM)

v. $\lambda \neq 0, \rho \neq 0$ the complete model (SARAR)

These five cases above will be reviewed in the following sections. First, let us consider a general condition on the model's parameters.

Equation (3.1) can be written as:

$$(I - lW)y = Xb_{(1)} + WXb_{(2)} + u$$

$$y = (I - lW)^{-1}\,[Xb + WXb + u] \quad (3.4)$$

substituting and simplifying 3.2and Equation (3.2) as:

$$u = (I - \rho W)\varepsilon^{-1} \quad (3.5)$$

provided that the two inverse matrices exist. Using the Gerschgorin (1931) theorem Kelejian and Prucha (1998) proved that, when the W matrix is row-standardized, both inverse matrices exist if $|r|<1$ and $|l|<1$, hence the parameters' restriction reported in Equations (3.1) and (3.2).

3.4.3 Pure Spatial Auto regression

Assume $b=0$ and either $=0$ λor $\rho=0$ in equation 3.4 and further assuming $e\ X \approx i.i.d.N(0,s^2\ onIn)$ and W non-stochastic, then the model reduces to a simple spatial auto regression that can be estimated via the ML procedure (Whittle, 1954).

In this case we have

$$y=\lambda Wy + \varepsilon|\lambda| < 1 \qquad (3.6)$$

when $\rho = 0$ or

$$y = \rho Wy + \varepsilon|\rho| < 1 \qquad (3.7)$$

Where W= Weighted Matrix, λ and ρ are the parameters to be estimated, $y$is the dependent variable and ε is the error term.

when $\lambda = 0$ since, in this instance, $y = u$. In this case we can derive the likelihood in the following way. Recall that from Equation (3.6) (or (3.7)) we have that:

$$(I- \rho W)y = \varepsilon$$

Hence the dependent variable y becomes;

$$y = (I-\rho W)^{-1}\ \varepsilon$$

which implies that the expectation of y, E(y) is;

$$E(y) = 0 \qquad (3.8)$$

While the variance can be written as;

$$E(yy^T)= \delta_\varepsilon^2(I-\rho W)^{-1}(I-\rho W^T)^{-1} =\delta_\varepsilon^2\ \Omega \quad (3.9)$$

Having assumed normality of the innovations, the likelihood function can therefore be expressed as:

$$L(\rho, \sigma_\varepsilon^2) = const(\sigma_\varepsilon^2)|\Omega| - \tfrac{1}{2} \exp\{- \tfrac{1}{2\sigma_\varepsilon^2} y^T \Omega^{-1} y\} \qquad (3.10)$$

Substituting the explicit expression for the matrix Ω reported in Equation (3.9), we can write:

$$L(\rho, \sigma_\varepsilon^2) = const(\sigma_\varepsilon^2)^{-\frac{1}{2}}|1 - \rho W)^{-1}(1 - \rho W)^{-T}|^{-\frac{1}{2}}$$

$$\times \exp\{-\frac{1}{2\sigma_\varepsilon^2}\gamma^T[(1 - \rho W)^{-1}(1 - \rho W)^{-T}]^{-1}\gamma\} \quad (3.11)$$

and, finally, the log-likelihood can be expressed as

$$l(\rho, \sigma_\varepsilon^2) = const\frac{n}{2}\ln(\sigma_\varepsilon^2) - \frac{1}{2}\ln|(1 - \rho W)^{-1}(1 - \rho W)^{-T}|$$

$$-\frac{1}{2\sigma_\varepsilon^2}\gamma^T[I - \rho W)^{-1}(1 - \rho W)^{-T}]^{-1}\gamma \quad (3.12)$$

3.5 The Classical Model with Spatially Lagged Non-Stochastic Regressors

When $\lambda = 0, \rho = 0$, if we further assume that $\varepsilon | X \approx i.i.d.N(0, \delta_n^2 I_n)$, that both X and W are non-stochastic and that the matrix of all regressors $Z = [X, WX]$ is full rank then the model only possibly contains a spatial lag of some or all the independent variables. In this situation no particular estimation problem emerges and the model can be simply estimated using the OLS procedure.

3.6 The Spatial Error Model (SEM)

When $\lambda = 0$ and $\rho \neq 0$, the Model becomes

$$y = Zb + u \quad (3.13)$$

$$u = \rho Wu + \varepsilon \; / \rho / < 1 \quad (3.14)$$

with the regressors Z and the weights W non-stochastic. This model is referred to in the literature as the Spatial Error Model (SEM) (Anselin, 1988; Arbia, 2006; LeSage and Pace, 2009)

If □ | $X \approx i.i.d.N(0,\delta_{\varepsilon n}^2 I_n)$, then we have that u=(I- $\rho W)^{-1}$ □ as in equation 3.5 so we can write:

$$E(u) = 0$$

$$E(uu^T) = \sigma_{□}^2 (I - \rho W)^{-1}(I - \rho W^T)^{-1} = \sigma_{□}^2 \Omega \quad (3.15)$$

a formulation that considers both heteroscedastic and autocorrelated error terms. In these circumstances the *GLS* procedure may be applied only if the value of the parameter *r* is known *a priori*, a circumstance which happens only very rarely in empirical cases. Notice that from Equation (3.14) we have

$$(I - \rho W)u = □ \quad (3.16)$$

and model (3.13) (3.14) can thus also be written as:

$$(I - \rho W)y = (I - \rho W)Zb + (I - \rho W)u$$

$$y = \rho Wy + Zb - WZ\rho b + □$$

$$y = \rho Wy + Z\beta - WZy + □ \quad (3.17)$$

3.7 A Primer for Spatial Econometrics

With $\lambda = \rho b$ and one may think of estimating model (3.76) directly. However, two problems emerge. First of all, Equation (3.17) is overparametrized due to the restriction $\gamma = \rho\beta$. Secondly, the term *Wy* is correlated with the error term, thus producing endogeneity. To convince ourselves of this let us consider that, from Equation (3.17):

$$(I - rW)y = Z\beta - WZg + □$$

and so,

$$E[(Wy)\,\varepsilon^T] = E[W(I-\rho W)^{-1}(Z\beta - WZy)$$

$$+W(I-\rho W)^{-1}\,\varepsilon]\varepsilon^T = W(I-\rho W)^{-1}(Zb - WZy)E(\varepsilon^T) \qquad (3.18)$$

$$+W(I-\rho W)^{-1}\,E[\,\varepsilon\varepsilon^T] = \sigma^2 W(I-rW)^{-1} I \neq 0$$

So the error is endogeneous, in that it is correlated with the spatially lagged variable *Wy*. As a consequence of the endogeneity of the errors, the OLS procedure loses its optimal properties.

In principle, an instrumental variable procedure could have been adopted to accommodate endogeneity. However, Kelejian and Prucha (1998) proved that such a procedure is not consistent due to the fact that it is not possible to identify instruments for *Wy* which are linearly independent of the other two regressors, *Z* and *WZ*.

3.8 The General SARAR(1,1) Model

3.8.1 Generalities

To start with, let us consider the case where, in Equations (3.1) and (3.2), we set $\beta = 0$. We have:

$$y = \lambda Wy + u \quad |\lambda| < 1 \qquad (3.19)$$

$$u = \rho Wu + \varepsilon \quad |\rho| < 1 \qquad (3.20)$$

we thus have:

$$(I - \lambda W)y = u \qquad y = (I - \lambda W)^{-1}u \qquad (3.21)$$

And

$$(I - \rho W)\,u = \varepsilon u = (I - \rho W)^{-1}\,\varepsilon \qquad (3.22)$$

Combining (3.21) and (3.22) we have:

$$y = (I - \lambda W)\,(I - \rho W)^{-1}\varepsilon \qquad (3.23)$$

$$E(yy^T) = E[(I-\lambda W)^{-1}(I-\rho W)^{-1}\varepsilon\varepsilon^T(I-\lambda W)^{-T}(I-\rho W)^{-T}]$$

$$= \sigma_\varepsilon^2(I-\lambda W)^{-1}(I-\rho W)^{-1}(1-\lambda W)^{-T}(I-\rho W)^{-T} \quad (3.24)$$

$$= \sigma_\varepsilon^2$$

so that the inverse of Ω is now:

$$\Omega^{-1} = (I-\lambda W^T)(I-\rho W^T)(I-\rho W)(I-\lambda W) \quad (3.25)$$

$$= [I-(\lambda+\rho)W^T + \lambda\rho W^T W^T]$$

$$X\ [\ I-(\lambda+\rho)W^T + \lambda\rho W^T W^T]^T$$

where the two parameters λ and ρ are present in the form of a sum and of a product and so they cannot be identified univocally. This fact has been considered in the literature to suggest that a complete model of the kind reported in Equations (3.19) and (3.20) is not feasible in practice. However, Kelejian and Prucha (1998) proved that this only happens when $\beta = 0$ and it is not the case conversely when $\beta \neq 0$, which is what usually happens in the generality of cases of interests in spatial econometrics. In this case we can define a more general spatial model which encompasses the Spatial Lag and the Spatial Error models previ- ously discussed in sections 3.3 and 3.4. This model, as already said, was termed a SARAR(1,1) model by Kelejian and Prucha (1998), but is also referred to in the literature as the *General Spatial Model* by Anselin (1988) or as an *SAC* model by LeSage and Kelly (2009).

If we consider the general SARAR model we thus have

$$y = Zb + \lambda Wy + u \qquad |\lambda| < 1 \quad (3.26)$$

$$u = \rho Wu + \varepsilon \quad |\rho| < 1 \quad (3.27)$$

$\varepsilon \mid X \approx i.i.d.N(0,\delta_{\varepsilon}^{2} I_n)$,

Model (3.26) and (3.27) presents two major estimation problems. First, similar to the case of the *SLM* examined in the previous section, we have a problem of endogeneity associated to the presence of the lagged term *Wy*. Secondly, due to the presence of the autoregression in the stochastic disturbance in Equation (3.27), we cannot employ a GLS strategy unless the parameter ρ is known. In this case we can exploit the following estimation alternatives:

i. Maximum Likelihood
ii. A spatial version of the Two-Stage Least Squares (GS2SLS)
iii. Lee's Instrumental Variable estimators (LIV)

Maximum likelihood is feasible, but presents the limitation that there is currently no formal proof that the estimators possess the usual optimal large sample properties. The GS2SLS estimators are not fully efficient. The LIV estimator achieves more efficient estimators than GS2SLS, even if the gain in efficiency is only limited. The three alternative estimators will be now discussed in turn.

3.10 Maximum Likelihood Estimator

Let us consider again the full model contained in Equations (3.1) and (3.2)

$$y = Z\beta + \lambda Wy + u \qquad |\lambda|<1 \tag{3.28}$$

$$u = \rho Wu + \varepsilon \quad |\rho|<1 \tag{3.29}$$

From Equation (3.70) we have

$$E(y) = (I-\lambda W)^{-1} Z\beta \tag{3.30}$$

and also

$$E(yy^{T}) = E[(I-\lambda W)(I-\rho W)^{-1}\varepsilon\varepsilon^{T}(I-\lambda W)^{-T}\}$$

$$=\sigma_\varepsilon^2 (1 - \lambda W)^{-1} (1 - \rho W)^{-1} (1 - \lambda W)^{-T} (1 - \rho W)^{-T} = \sigma_\varepsilon^2 \Omega \quad (3.31)$$

Therefore, maintaining the hypothesis of normality on the disturbances, we would have:

$$Y \approx N [(1 - \lambda W)^{-1} X\beta \sigma_\varepsilon^2 \Omega] \quad (3.3)$$

3.11Interpretation of The Parameters in Spatial Econometric Models

In a standard linear regression model the regression parameters have an easy interpretation in that they represent the partial derivative of the dependent variable y with respect to the independent variables:

$$b_i = \frac{\partial}{\partial X_i} y_i \quad (3.32)$$

they can therefore be straightforwardly interpreted as the variation induced on variable y of a unitary increase in the single independent variable X_i.

However, in the spatial econometric models presented in this chapter the interpretation of the parameters is less immediate and requires some clarification. In fact, a variation of variable X observed in location i does not only have an effect on the value of variable y in the same location, but also on variable y observed in other locations. Recall Okun's Law model: that an increase in the level of GDP produces anincrease in the level of unemployment. Consider also, for simplicity, a Spatial Lag model. The model can be expressed as follows:

$$\Delta unempl_i = b_0 + b_1 \Delta GDP_i + l \sum_{j=1}^{n} W_{ij} \Delta unempl_j \quad (3.33)$$

In this case, an increase in the *GDP* in region *i* produces as an immediate effect, a decrease in the level of unemployment in that region. However, given the spatial autoregressive mechanism considered in this framework, the variation of the level of unemployment in region *i*, also produces an effect on the level of unemployment in other neighboring regions so that all impacts have to be evaluated simultaneously. This topic has been treated in the literature by Kelejian et al. (2006) and LeSage and Pace (2009) amongst others. The formal solution to the problem consists of evaluating the partial derivative (3.32) in each specific model. Consider, for example, the case of the Spatial Lag model:

$$y = lWy + Xb + u \qquad |l| < 1 \tag{3.34}$$

which can also be written in the reduced form as:

$$y = (I - lW)^{-1} Xb + (I - lW)^{-1} u \tag{3.35}$$

which implies:

$$E(y) = (I - lW)^{-1} \text{ Xb} \tag{3.36}$$

The impact of each variable X on y can then be described through the partial derivatives $\frac{\partial E(y)}{\partial X}$ which can be arranged in the following matrix:

$$\frac{\partial E(y)}{\partial X} = \text{S} = \begin{bmatrix} \frac{\partial E(y_1)}{\partial X_1} & \cdots & \frac{\partial E(y_1)}{\partial X_n} \\ \cdots & \cdots & \cdots \\ \frac{\partial E(y_n)}{\partial X_1} & \cdots & \frac{\partial E(y_n)}{\partial X_n} \end{bmatrix} \tag{3.37}$$

whose single entry is defined as:

$$\text{S}_{ij} = \frac{\partial E(y_i)}{\partial X_J} \tag{3.38}$$

Based on Lasage and Pace (2009) who suggested and employed the following impact measures that can be calculated for each of the independent variables X_i included in the model:

1. A global measure, termed Average Direct Impact (ADI). This measure refers to the average total impact of a change in X_I on y_i for each observation, which is implies that the average of all diagonal entries in matrix S:

$$ADI = n^{-1} tr(S) = \sum_{i=1}^{n} \frac{\partial E(y_i)}{\partial X_i} \quad (3.39)$$

2. The Average Total Impact to an observation (ATIT) which is the measure of the impact produced on a single observation by all the other observation is calculated as the sum of the i^{th} row matrix S:

$$ATTIT_i = n^{-1} \sum_{i=1}^{n} S_{ij} = n^{-1} \sum_{i=1}^{n} \frac{\partial E(y_i)}{\partial X_i} \quad (3.40)$$

3. A measure related to the impact produced by one single observation on all other observations, termed *Average Total Impact From* (ATIF)an observation. For each observation this is calculated as the sum of the *j*-th column of matrix *S*:

$$ATIF_i = n^{-1} \sum_{j=1}^{n} S_{ij} = n^{-1} \sum_{j=1}^{n} \frac{\partial E(y_i)}{\partial X_j} \quad (3.41)$$

4. A global measure of the average impact obtained from the two preceding measures:

$$ATI = n^{-1} i^{T} Si = n^{-1} \sum_{j=i}^{n} ATIT_i = n^{-1} \sum_{j=i}^{n} ATIF_I \quad (3.42)$$

Which is the Average of all of matrix S.

5. A measure of the average indirect impact obtained as the differ- ence between ATI and ADI:

$$AII = ATI - ADI \quad (3.43)$$

Which is the average of all the Off – diagonal entries of matrix S.

Measures of relative impact for a general *SARAR* model can be similarly obtained by substituting the appropriate reduced form expressions in Equation (3.35) .

3.12R Codes: Estimating Linear Spatial Models

All the R commands related to the procedures described in this chapter are contained in the library spdep. All the commands are very similar to the standard commands for regressions and are very straightforward to apply.

In all cases we assume that we want to estimate the basic model:

$y = b_0 + b_1 x + b_2 z + e$

CHAPTER FOUR

DATA PRESENTATION AND ANALYSIS

The Data that was obtained from National Bureau of Statistics Bulletin (NBS), 2017 - 2018 and from – https://stateofstates.kingmakers.com.ng.

4.1 Data Presentation and Result on Okun's Law

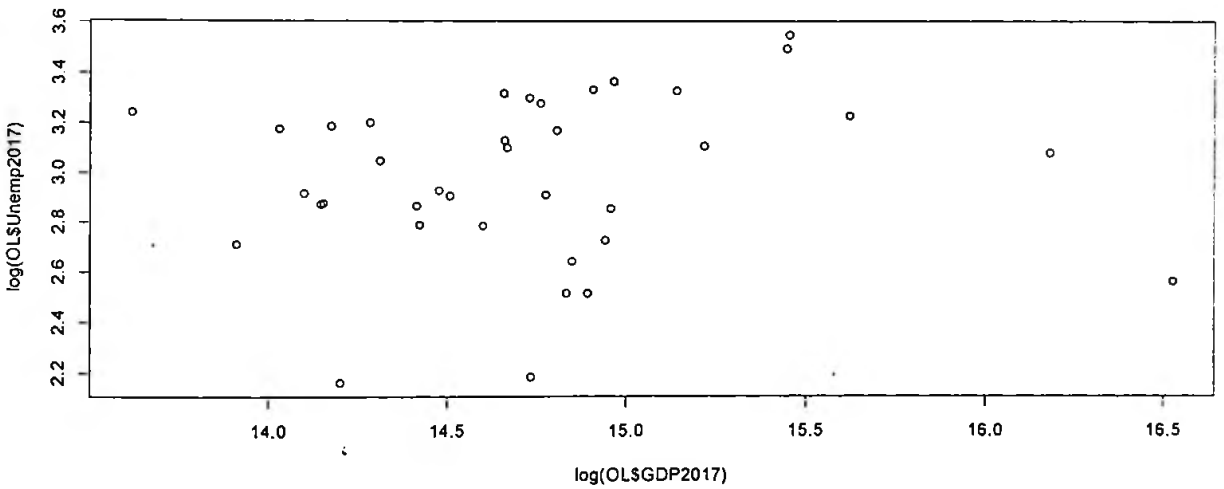


Fig 4.1: Scattered Plot Between GDP and Unemployment in all the States in Nigeria in 2017 - 2018.

From Fig 4.1, the scattered plot also shows no significant relationship which is a negative relationship between Unemployment and GDP in Nigeria.

Table 4.1: Result on Okun's Law in Nigeria

Parameters	OLS	SPARTIAL LAG MODEL	SPATIAL LAG (MIXED)	SPATIAL ERROR MODEL	SPATIAL ERROR MODEL (GLS)	SARAR 2SLS	SARAR (G2SLS
Intercept	2.08211	0.3531	0.6525	2.6077	2.5814	-1.6584	0.3531
GDP	0.06123	0.0426	0.0221.	0.0269	0.0285	0.0285	0.0426
Lag (GDP)			0.0909				
ADI		0.0497	0.0478				0.0497
AII		0.0809	0.02898				0.0809
ATI		0.1306	0.3375				0.1306

In table 4.1 above, the result from OLS shows that there is a positive relation between unemployment and GDP in Nigeria. One unit increase in GDP leads to increase of 0.06123 unit increase in Unemployment rate in Nigeria which contradicts Okuns Law.The intercepts and the GDP are not significant (P> 0.05) . In addition, the OLS has a weak R-squared of 1.195%.

The Durbin-Watson Test for autocorrelation with the residual reveal the presence of autocorrelation in the OLS Residual (P< 0.05). the implication of this is that there could be evidence of the effect of spatial autocorrelation in the model.

The Heteroscedasticity test using studentized Breusch -pagan test reveal the absence of Heteroscedasticity in the OLS regression model (P> 0.05)

Lastly, the normality test of the residual using JarqueBera Test that the residual is normally distributed (P> 0.05).

To carry out analysis on spatial econometrics, there is need to test for the Prescence of Spatial autocorrelation using the Moran I Test.

The Moran test reveal the Prescence of Spatial Autocorrelation ($P< 0.05$). in addition, the Monte-Carlo simulation of Moran I the Prescence of Spatial autocorrelation ($P< 0.05$).

In addition, using the Langrange Multiplier diagnostics test for spatial dependence such as LMerr, LMlag, SARMA, reveal that all are significant as ($P< 0.05$) while RLMerr and RLMlag are not significant ($P> 0.05$).

For the Spatial Lag Model, the coefficient reveals positive relationship, but the coefficient is not significant ($P>0.05$). furthermore, the LM test for Residual autocorrelation reveal the absence of spatial autocorrelation as ($P> 0.05$). the implication is that the spatial lag Model has taken care of the effect of spatial autocorrelation.

In addition, result from Spatial Lag Modelshows a unit increase in GDP leads to an increase of 0.0497 increases in Unemployment rate in Nigeria. In addition, a unit increase of GDP in one state of Nigeria produces a total impact of increment of 0.1306 in Unemployment rate.

For the Spatial Lag (Mixed) Model, the coefficient reveals positive relationship, but the coefficient is not significant ($P> 0.05$). furthermore, the LM test for Residual autocorrelation reveal the absence of Spatial autocorrelation as ($P> 0.05$). the implication is that the spatial lag (Mixed) Model has taken care of the effect of spatial autocorrelation.

In addition, result from Spatial Lag (Mixed) Modelshows a unit increase in GDP leads to an increase of 0.0478 increases in Unemployment rate in Nigeria. In addition, a unit increase of GDP in one state of Nigeria produces a total impact of increment of 0.3375 in Unemployment rate.

For the Spatial Error Model, the coefficient reveals positive relationship but the coefficient are not significant ($P> 0.05$).

For the Spatial Error (GLS) Model, the coefficient reveals positive relationship, but the coefficient is not significant ($P>0.05$).

For the SARAR (2SLS) Model, the coefficient reveals positive relationship, but the coefficient is not significant (P>0.05).

For the SARAR (GS2SLS) Model, the coefficient reveals positive relationship. but the coefficient is not significant (P>0.05).

In addition, result from SARAR(GS2SLS)shows a unit increase in GDP leads to an increase of 0.0497 increases in Unemployment rate in Nigeria. In addition, a unit increase of GDP in one state of Nigeria produces a total impact of increment of 0.1306 in Unemployment rate.

4.2 Discussion of Result For Okun's Law

In table 4.1 above, the result from OLS shows that there is a positive relation between unemployment and GDP in Nigeria. One unit increase in GDP leads to increase of 0.06123 unit increase in Unemployment rate in Nigeria which contradicts Okuns Law.The intercepts and the GDP are not significant (P> 0.05) . In addition, the OLS has a weak R-squared of 1.195%. the implication of this result shows that the Okun's Law does not hold in Nigeria. This result agrees with the following works Adenomon& Tela (2017); Okoro-Ugochukwu and Adenomon (2021B); Sodipe and Ogunriola (2011); Arewa and Nwakanma(2012); Babalola Saka and Adenuga (2013); Abraham (2014);Akeju and Olanipekun (2014). However, our result contradicts other works from other countries especially developed countries of Higgins (2011).

The Durbin-Watson Test for autocorrelation with the residual reveal the presence of autocorrelation in the OLS Residual (P< 0.05). The implication of this is that there could be evidence of the effect of spatial autocorrelation in the model.

The Heteroscedasticity test using studentized Breusch -pagan test reveal the absence of Heteroscedasticity in the OLS regression model (P> 0.05). The implication is that the error is Homoscedasticity.

Lastly, the normality test of the residual using Jarque Bera Test, that the residual is normally distributed (p greater than 0.05). In all, the OLS met the condition of Homoscedasticity, normality test but failed the spatial autocorrelation test.

The Moran test reveals the Prescence of Spatial Autocorrelation (P< 0.05). in addition, the Monte-Carlo simulation of Moran I reveal the Prescence of Spatial autocorrelation (P< 0.05). In addition, using the Langrange Multiplier diagnostics test for spatial dependence such as LMerr, LMlag, SARMA, reveal that all are significant as (P< 0.05) while RLMerr and RLMlag are not significant (P> 0.05). The implication of this result provides the basis for Spatial regression Models.

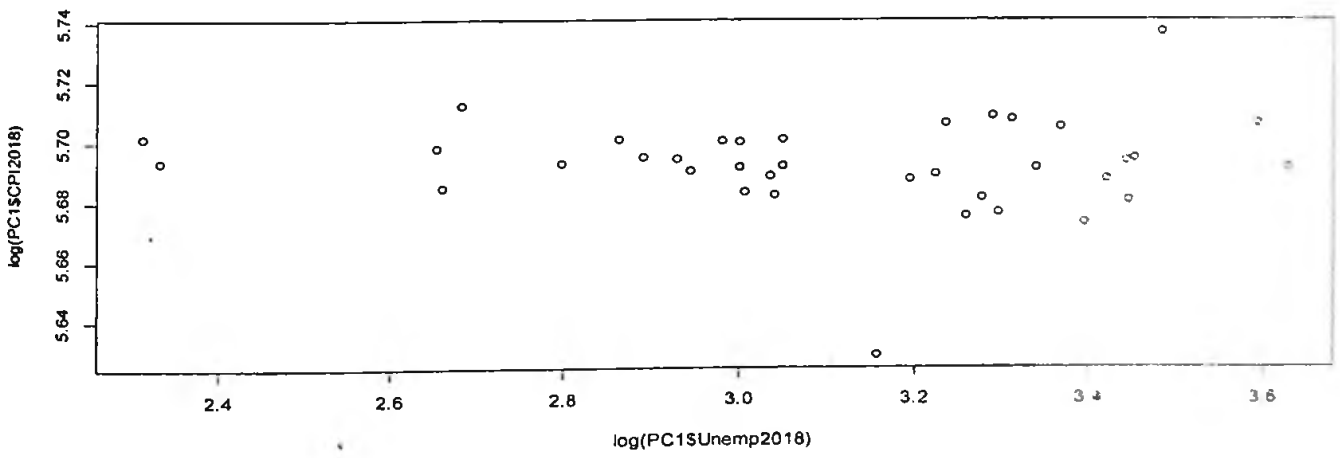
For the Spatial Lag Model, the coefficient reveals positive relationship, but the coefficient is not significant (P> 0.05). furthermore, the LM test for Residual autocorrelation reveal the absence of spatial autocorrelation as (P> 0.05). the implication is that the spatial lag Model has taken care of the effect of spatial auto correlation. In addition, result from Spatial Lag Model shows a unit increase in GDP leads to an increase of 0.0497 increases in Unemployment rate in Nigeria. In addition, a unit increase of GDP in one state of Nigeria produces a total impact of increment of 0.1306 in Unemployment rate. This result agrees with the following works (Adenomon& Tela (2017); Okoro-Ugochukwu and Adenomon (2021B); Sodipe and Ogunriola (2011); Arewa and Nwakanma (2012); Babalola Saka and Adenuga (2013); Abraham (2014); Akeju and Olanipekun (2014). However, our result contradicts other works from other countries especially developed countries.

For the Spatial Lag (Mixed) Model, the coefficient reveals positive relationship, but the coefficient is not significant (P>0.05). further rmore, the LM test for Residual autocorrelation reveal the absence of Spatial autocorrelation as (P> 0.05). The implication is that the spatial lag (Mixed) Model has taken care of the effect of spatial autocorrelation. In addition, result from Spatial Lag (Mixed) Model shows a unit increase in GDP leads to an increase of 0.0478increases in Unemployment rate in Nigeria. In addition, a unit increase of GDP in one state of Nigeria produces a total impact of increment of 0.3375 in Unemployment rate. This result agrees with the following works Adenomon& Tela (2017); Okoro-Ugochukwu and Adenomon (2021B); Sodipe and Ogunriola (2011); Arewa and Nwakanma (2012); Babalola Saka and Adenuga (2013); Abraham (2014); Akeju and Olanipekun (2014). However, our result contradicts other works from other countries especially developed countries.

For the Spatial Error Model, the coefficient reveals positive relationship, but the coefficient is not significant (P>0.05). For the Spatial Error (GLS) Model, the coefficient reveals positive relationship, but the coefficient is not significant (P> 0.05). This result agrees with the following works Adenomon& Tela (2017); Okoro-ugochukwu and Adenomon (2021B); Sodipe and Ogunriola (2011); Arewa and Nwakanma (2012); Babalola Saka and Adenuga (2013); Abraham (2014) ;Akeju and Olanipekun (2014) . However, our result contradicts other works from other countries especially developed countries.

For the SARAR (2SLS) Model, the coefficient reveals positive relationship, but the coefficient is not significant (P> 0.05). For the SARAR (GS2SLS) Model, the coefficient reveals positive relationship, but the coefficient is not significant (P> 0.05). In addition, result from SARAR(GS2SLS)shows a unit increase in GDP leads to an increase of 0.0497 increases in Unemployment rate in Nigeria. In addition, a unit increase of GDP in one state of Nigeria produces a total impact of increment of 0.1306 in Unemployment rate. This result agrees with the following works Adenomon& Tela (2017); Sodipe and Ogunriola (2011); Arewa and Nwakanma (2012); Babalola Saka and Adenuga (2013); Abraham (2014) ;Akeju and Olanipekun (2014); Okoro-Ugochukwu and Adenomon (2021B)). However, our result contradicts other works from other countries especially developed countries

4.3 Data Presentation and Analysis of Phillip's Curve



Parameters	OLS	SPARTIAL LAG MODEL	SPATIAL LAG (MIXED)	SPATIAL ERROR MODEL (ML)	SPATIAL ERROR MODEL (GLS)	SARAR 2SLS	SARAR GS2SLS
Intercept	5.6985	4.4108	4.4194	5.6960	5.6962	-7.7776	4.4108
Unemployment	-0.0019	-0.0011	-0.0005	-0.0011	-0.0011	0.0071	-0.0011
Lag(Unemployment)			-0.0012				
ADI		-0.0011	-0.0006				0.0478
AII		-0.0003	-0.0016				0.02897
ATI		-0.0014	-0.0022				0.3375

Fig 4.2: Scattered plot between Inflation and Unemployment in all the states in Nigeria in 2017 - 2018

Table 4.2: Result on Phillip's Curve In Nigeria

In table 4.2 above, the result from OLS shows that there is a negative relation between unemployment and Inflation in Nigeria. One unit decrease in inflation leads to of – 0.0019 unit decrease in Unemployment rate in Nigeria which agrees with Phillips curve. The intercepts and the Unemployment are significant (P< 0.05). In addition, the OLS has a weak R-squared of 0.1419%.

The Durbin-Watson Test for autocorrelation with the residual reveal the absence of autocorrelation in the OLS Residual (P> 0.05). the implication of this is that there no evidence of any effect of spatial autocorrelation in the model.

The Heteroscedasticity tests using studentized Breusch -pagan test reveal the absence of Heteroscedasticity in the OLS regression model (P> 0.05)

Lastly, the normality test of the residual using JarqueBera Test that the residual is not normally distributed (P< 0.05).

To carry out analysis on spatial econometrics, there is need to test for the Presecence of Spatial autocorrelation using the Moran I Test.

The Moran test reveal the Prescence of Spatial Autocorrelation (P< 0.05) which shows the Prescence of spatial autocorrelation at 10%. in addition, the Monte-Carlo simulation of Moran I reveal the Prescence of Spatial autocorrelation (P< 0.05).

In addition, using the Langrange Multiplier diagnostics test for spatial dependence such as LMerr, LMlag,RLMerr, RLMlag, SARMA, the result reveal that all are not significant as (P> 0.05).

For the Spatial Lag Model, the coefficient reveals positive relationship,andthe coefficient are significant (P< 0.05). Furthermore, the LM test for Residual autocorrelation reveal the absence of spatial autocorrelation as (P> 0.05). the implication is that the spatial lag Model has taken care of the effect of spatial autocorrelation.In addition, result from Spatial Lag Modelshows a unit decrease in Inflation leads to an decrease of – 0.0011decrease in Unemployment rate in Nigeria. In addition, a unit decrease ofInflation in one state of Nigeria produces a total impact of reduction of -0.0014 reduction in Unemployment rate.

For the Spatial Lag (Mixed) Model, the coefficient reveals positive relationship, but the coefficient is not significant (P< 0.05). Furthermore, the LM tests for Residual autocorrelation reveal the absence of Spatial autocorrelation as (P> 0.05). The implication is that the spatial lag (Mixed) Model has taken care of the effect of spatial autocorrelation. In addition, result from Spatial Lag (Mixed) Model shows a unit decrease in Inflation leads to decrease of -0.0006 decrease in Unemployment rate in Nigeria. In addition, a unit decrease of Inflation in one state of Nigeria produces a total impact of reduction of -0.0022 in Unemployment rate.

For the Spatial Error Model, the coefficient reveals negative relationship and the coefficient are also significant (P> 0.05). For the Spatial Error (GLS) Model, the coefficient reveals negative relationship, but the coefficient is not significant (P> 0.05).

For the SARAR (2SLS) Model, the coefficient reveals negative relationship, but the coefficient is not significant (P> 0.05). For the SARAR (GS2SLS) Model, the coefficient reveals negative relationship, but the coefficient is not significant (P> 0.05). In addition, result from

SARAR(GS2SLS)shows a unit decrease in Inflation leads to a decrease of -0.0011 decrease in Unemployment rate in Nigeria. In addition, a unit decrease of Inflation in one state of Nigeria produces a total impact of increment of 0.3375 in Unemployment rate.

4.4 Discussion of Result on Phillip's Curve

In table 4.2, the result from OLS shows that there is a negative relation between unemployment and Inflation in Nigeria. One unit decrease in inflation leads to of – 0.0019 unit decrease in Unemployment rate in Nigeria which agrees with Philips curve hypothesis. The intercepts and the Unemployment are significant (P< 0.05). In addition, the OLS has a weak R-squared of 0.1419%. This result agrees with Okoro-Ugochukwu and Adenomon (2021A);Orji et al (2015); Ezeaku and Ugwuebe (2016) but contradicts the work of Iyeh and Edeme (2017).

The Durbin-Watson Test for autocorrelation with the residual reveals the absence of autocorrelation in the OLS Residual (P> 0.05). The implication of this is that there no evidence of any effect of spatial autocorrelation in the model.
The Heteroscedasticity test using studentized Breusch - pagan test reveal the absence of Heteroscedasticity in the OLS regression model (P> 0.05)

Lastly, the normality test of the residual using JarqueBera Test that the residual is not normally distributed (P< 0.05).

To carry out analysis on spatial econometrics, there is need to test for the Prescence of Spatial autocorrelation using the Moran I Test.
The Moran test reveal the Prescence of Spatial Autocorrelation (P< 0.05) which shows the Prescence of spatial autocorrelation at 10%. in addition, the Monte-Carlo simulation of Moran I reveal the Prescence of Spatial autocorrelation (P< 0.05).

In addition, using the Langrange Multiplier diagnostics test for spatial dependence such as LMerr, LMlag, RLMerr, RLMlag, SARMA, the result reveal that all are not significant as (P> 0.05).

For the Spatial Lag Model, the coefficient reveals positive relationship,and the coefficient are significant (P< 0.05). Furthermore, the LM test for Residual autocorrelation reveal the absence of spatial autocorrelation as (P> 0.05). the implication is that the spatial lag Model has taken care of the effect of spatial autocorrelation. In addition, result from Spatial Lag Model shows a unit decrease in Inflation leads to an decrease of – 0.0011decrease in Unemployment rate in Nigeria. In addition, a unit decrease of Inflation in one state of Nigeria produces a total impact of reduction of -0.0014 reduction in Unemployment rate. This result agrees with the work of Okoro-Ugochukwu and Adenomon (2021A); Iyeh and Edeme (2017); Ezeaku and Ugwuebe (2016) but contradicts the work of Orji et al (2015).

For the Spatial Lag (Mixed) Model, the coefficient reveals positive relationship, but the coefficient is not significant (P< 0.05). furthermore, the LM test for Residual autocorrelation reveal the absence of Spatial autocorrelation as (P> 0.05). The implication is that the spatial lag (Mixed) Model has taken care of the effect of spatial autocorrelation. In addition, result from Spatial Lag (Mixed) Modelshows a unit decrease in Inflation leads to adecrease of -0.0006decrease in Unemployment rate in Nigeria. In addition, a unit decrease of Inflation in one state of Nigeria produces a total impact of reduction of -0.0022 in Unemployment rate. This result agrees with the work of Okoro-Ugochukwu and Adenomon (2021A); Orji et al (2015); Ezeaku and Ugwuebe (2016) but contradicts the work of Iyeh and Edeme (2017).

For the Spatial Error Model, the coefficient revealsnegativerelationship, and the coefficient are also significant (P> 0.05). For the Spatial Error (GLS) Model, the coefficient reveals negative relationship, but the coefficient is not significant (P> 0.05). For the SARAR (2SLS) Model, the coefficient reveals negative relationship, but the coefficient is not significant (P> 0.05). For the SARAR (GS2SLS) Model, the coefficient reveals negative relationship, but the coefficient is not significant (P> 0.05). In addition, result from SARAR(GS2SLS)shows a unit decrease in Inflation leads to a decrease of -0.0011 decrease in Unemployment rate in Nigeria. In addition, a unit decrease of Inflation in one state of Nigeria produces a total impact of increment of 0.3375 in Unemployment rate. This result agrees with the work of Okoro-Ugochukwu and Adenomon (2021A); Orji et al (2015), Ezeaku and Ugwuebe (2016) but contradicts the work of Iyeh and Edeme (2017).

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATION

5.1 Summary

5.1.1 Summary of Findings for Okun's Law

The result from OLS shows that there is a positive relation between unemployment and GDP in Nigeria. One unit increase in GDP leads to increase of 0.06123 unit in Unemployment rate in Nigeria which contradicts Okun's Law (Adenomon &Tela, 2017). This result disagrees with Schnabel, (2002). In addition, result from Spatial Lag Model shows a unit increase in GDP leads to an increase of 0.0497 in Unemployment rate in Nigeria. In addition, a unit increase of GDP in one state of Nigeria produces a total impact of increment of 0.1306 in Unemployment rate. This result contradicts Okuns Law (Adenomon &Tela, 2017) because based on their findings, when GDP increases, unemployment also increase.

Recall that in Okun' Law (1962), states that if the unemployment rate falls to 1%, then the output will be increased by 3%. Therefore, to avoid losses from unemployment, the economy should expand continuously. An important conclusion of the Okun's law is that actual GDP must grow faster than potential GDP. Okun's law provides the vital link between the market of goods and services and the labor market. He describes the association between short-term movements of real GDP and changes in unemployment.

5.1.2 Summary of Findings for Phillip's Curve

The result from OLS shows that there is a negative relation between unemployment rate and Inflation rate in Nigeria. One unit increase in Unempolyment rate leads to decrease of -0.0019 unit in Inflation rate in Nigeria which agrees Resurreccion et. al (2016) because by their findings.

it shows that an increase in the inflation rate or economic growth can cause the unemployment rate to reduce.

In addition, result from Spatial Lag Model shows a unit increase in Unemployment leads to decrease of 0.0011 of Inflation rate in Nigeria. In addition, a unit increase of Unemployment in one state of Nigeria produces a total impact of reduction of 0.0014 in Inflation rate. This result agrees with Phillip's curve rule since Phillip's curve has an inverse relationship with unemployment.

5.2 Conclusion

The study concludes Okun's law is contradicted in Nigeria economy while phillip's Curves agrees with the findings in Nigeria Economy. The implication is that while Okun's Law cannot be applied to Nigerian economy, Phillips's curve can be applied in Nigerian economy.

5.3 Recommendations

Based on the findings of this research work, the following recommendations were made:

i. Inflation rate should be checked by ensuring goods and services are not unnecessarily high or increased which can in turn trigger inflation.

ii. There is need for Government to create more entrepreneurs like SME (Small and Medium enterprises) for the citizens which will reduce unemployment drastically.

iii. More sectors of the economy that has been dead need to be resuscitated to accommodate more unemployed graduates.

5.4 Limitation of the Study

The data set used was only from 2017 - 2018 because the data for 2019 and 2020 are readily not available from Nigerian statistical Bulletin and Central Bank of Nigeria.

5.5 Contribution to Knowledge

This sturdy has been able to make the following contributions

i. The sturdy has been able to utilize Spatial models to analyze the cross-sectional data set which gave a more robust result.

ii. It has also been able to identify the presence of Spatial autocorrelation in Phillip's curve and Okun's law equation in the Nigerian macro-economic data.

5.6 Suggestion for Further study

These studies suggest further research with Spatial models to analyze Spatial panel data set

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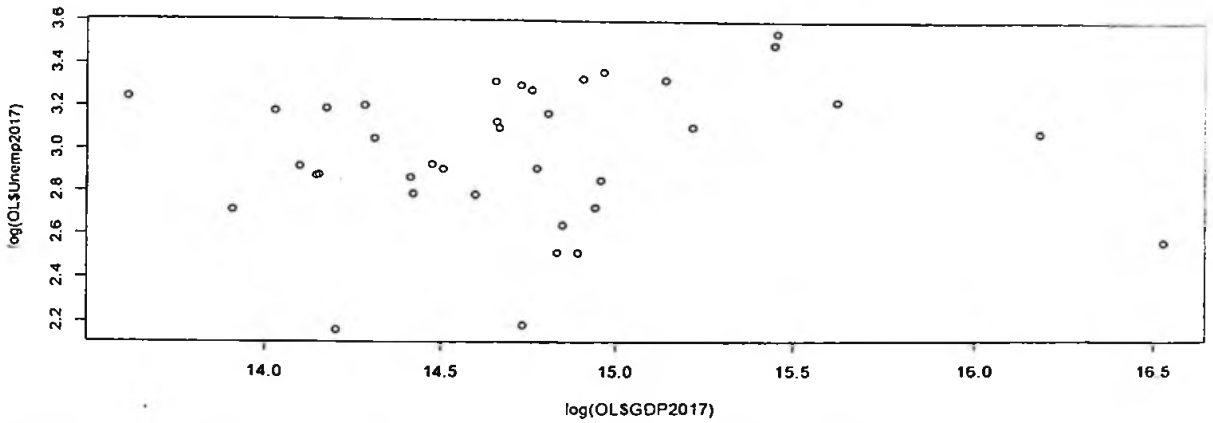
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States	Unemp2018	CPI2018	Unemp2017	GDP2017
Sokoto	26	291.6	22.9	2321435
Zamfara	18	297.4	15.1	1100458
Katsina	14.3	294.4	12.4	2769066
Jigawa	26.5	293.3	24.2	1431567
Yobe	29	300.4	25.6	822391.7
Borno	31.4	293.1	27.1	2487995
Adamawa	20.8	295.5	18.3	1993519
Gombe	27	291.9	24	1239249
Bauchi	23.5	278.2	21.1	1641327
Kano	31.3	297	28.1	2974429
Kaduna	26.8	301.5	23.8	2691446
Kebbi	20.1	296.4	17.8	1400148
Niger	20.9	293.7	18.4	2606186
FCT	24.4	295.2	21.7	10627398
Nasarawa	27.4	301.1	24.6	1592733
Plateau	29.8	290.9	26.6	2566070
Taraba	19	296	16.3	1832164
Benue	20.1	298.9	17.4	3128212
Kogi	19.7	299	17.6	1817777
Kwara	21.1	299.2	18.7	1936264
Oyo	10.3	297	8.9	2506754
Osun	10.1	299.3	8.7	1469983
Ekiti	20.2	293.9	17.7	1390020
Ondo	14.2	298.3	12.4	2933433
Edo	25.1	295.7	22.2	2342758
Anambra	17.5	299.2	15.3	3079167
Enugu	18.7	297.2	16.2	2186105
Ebonyi	21.1	296.5	18.5	1327104
Cross-River	30.6	295.2	27.6	2314949
Akwa Ibom	37.7	296.3	34.9	5141068
Abia	31.6	297.2	27.9	3763223
Imo	28.2	296.3	25.2	6079483
Rivers	36.4	300.7	33	5110584
Bayelsa	32.6	310.1	29	3155779
Delta	25.4	300.7	22.4	4057812
Lagos	14.6	302.6	13	15063301
Ogun	16.4	296.8	14.1	2810277

Appendix A
Cross Sectional Data on Unemployment (2018 - 2017) and CPI and GDP for 2017

Source: NBS (2017 and 2018); https://stateofstates.kingmarkers.com.ng

Appendix B




```
OLreg<-lm(log(Unemp2017)~log(GDP2017),data=OL)
>summary(OLreg)

Call:
lm(formula = log(Unemp2017) ~ log(GDP2017), data = OL)

Residuals:
     Min       1Q   Median       3Q      Max
-0.79821 -0.17390  0.00461  0.24625  0.52424

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)   2.08211    1.38712   1.501    0.142
log(GDP2017)  0.06123    0.09409   0.651    0.519

Residual standard error: 0.3338 on 35 degrees of freedom
Multiple R-squared:  0.01195,   Adjusted R-squared:  -0.01628
F-statistic: 0.4234 on 1 and 35 DF,  p-value: 0.5195


Durbin-Watson test

data:  OLreg
DW = 1.029, p-value = 0.000561
alternative hypothesis: true autocorrelation is greater than 0

bptest(OLreg)


studentizedBreusch-Pagan test

data:  OLreg
```

```
BP = 0.7858, df = 1, p-value = 0.3754

jarque.bera.test(OLreg$residuals)

JarqueBera Test

JarqueBera Test

data:  OLreg$residuals
X-squared = 3.0337, df = 2, p-value = 0.2194

> W1
Characteristics of weights list object:
Neighbour list object:
Number of regions: 37
Number of nonzero links: 172
Percentage nonzero weights: 12.56392
Average number of links: 4.648649

Weights style: W
Weights constants summary:
nnn S0       S1       S2
W 37 1369 37 17.63415 154.4067

lm.morantest(OLreg,W1)

        Global Moran I for regression residuals

data:
model: lm(formula = log(Unemp2017) ~ log(GDP2017), data = OL)
weights: W1

Moran I statistic standard deviate = 4.6039, p-value = 2.073e-06
alternative hypothesis: greater
sample estimates:
Observed Moran I      Expectation         Variance
      0.44565764      -0.03507805       0.01090336



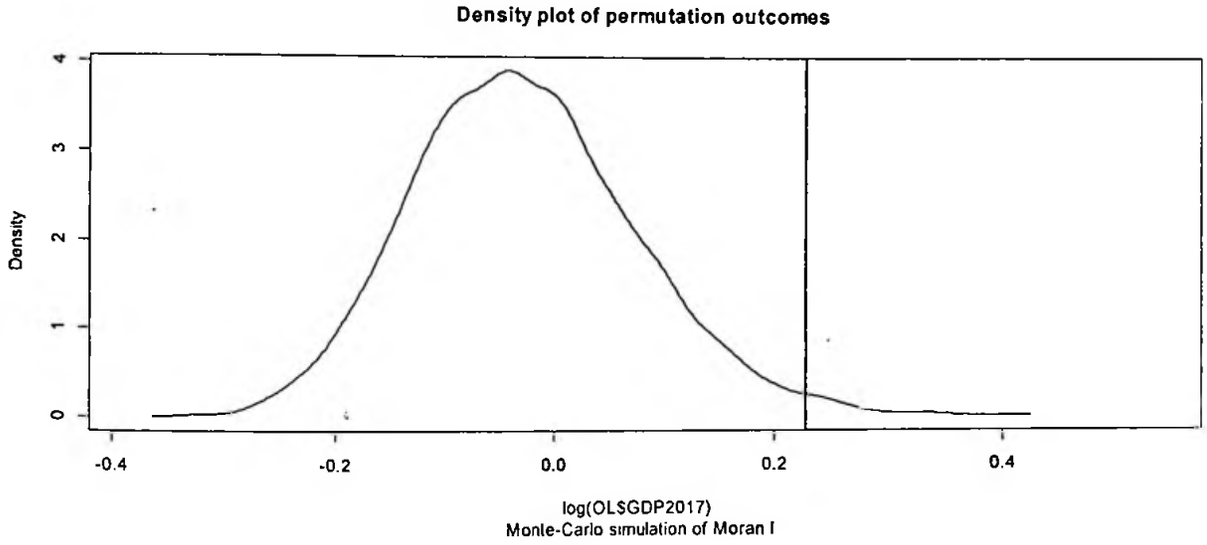
MC<-moran.mc(log(OL$GDP2017),W1,nsim=10000)
> MC

Monte-Carlo simulation of Moran I

data:  log(OL$GDP2017)
```

```
weights: W1
number of simulations + 1: 10001

statistic = 0.22773, observed rank = 9867, p-value = 0.0134
alternative hypothesis: greater
```




```
> LM<-lm.LMtests(OLreg,W1,test="all")
>summary(LM)
        Lagrange multiplier diagnostics for spatial dependence
data:
model: lm(formula = log(Unemp2017) ~ log(GDP2017), data = OL)
weights: W1

statistic parameter   p.value
LMerr    15.41884         1 8.613e-05 ***
LMlag    15.89945         1 6.680e-05 ***
RLMerr    0.41512         1 0.5193809
RLMlag    0.89574         1 0.3439271
SARMA    16.31458         2 0.0002866 ***
---
Signif.codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> LM

Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = log(Unemp2017) ~ log(GDP2017), data = OL)
weights: W1
```

```
LMerr = 15.419, df = 1, p-value = 8.613e-05


        Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = log(Unemp2017) ~ log(GDP2017), data = OL)
weights: W1

LMlag = 15.899, df = 1, p-value = 6.68e-05


        Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = log(Unemp2017) ~ log(GDP2017), data = OL)
weights: W1

RLMerr = 0.41512, df = 1, p-value = 0.5194


        Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = log(Unemp2017) ~ log(GDP2017), data = OL)
weights: W1

RLMlag = 0.89574, df = 1, p-value = 0.3439


        Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = log(Unemp2017) ~ log(GDP2017), data = OL)
weights: W1

SARMA = 16.315, df = 2, p-value = 0.0002866
```

Spatial Lag Models for Okun's Law in Nigeria

```
> model1<-lagsarlm(log(Unemp2017)~log(GDP2017),data=OL,listw=W1)
Warning message:
Function lagsarlm moved to the spatialreg package
> model2<-
lagsarlm(log(Unemp2017)~log(GDP2017),data=OL,listw=W1,type="mixe
d")
Warning message:
```

```
Function lagsarlm moved to the spatialreg package
>summary(model1)

Call:spatialreg::lagsarlm(formula = formula, data = data, listw
= listw,
na.action = na.action, Durbin = Durbin, type = type, method =
method,
quiet = quiet, zero.policy = zero.policy, interval = interval,
tol.solve = tol.solve, trs = trs, control = control)

Residuals:
      Min        1Q    Median        3Q       Max
-0.567549 -0.146463  0.062137  0.208034  0.338727

Type: lag
Coefficients: (asymptotic standard errors)
             Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.353122   1.094200  0.3227   0.7469
log(GDP2017) 0.042581   0.070615  0.6030   0.5465

Rho: 0.67407, LR test value: 14.383, p-value: 0.00014916
Asymptotic standard error: 0.13005
z-value: 5.1833, p-value: 2.1802e-07
Wald statistic: 26.866, p-value: 2.1802e-07

Log likelihood: -3.6806 for lag model
ML residual variance (sigma squared): 0.062603, (sigma: 0.25021)
Number of observations: 37
Number of parameters estimated: 4
AIC: 15.361, (AIC for lm: 27.744)
LM test for residual autocorrelation
test value: 0.24181, p-value: 0.6229

> impact1<-impacts(model1,listw=W1)
Warning message:
Method impacts.sarlm moved to the spatialreg package
> impact1
Impact measures (lag, exact):
                 Direct   Indirect     Total
log(GDP2017) 0.04974732 0.08089618 0.1306435
>summary(model2)

Call:spatialreg::lagsarlm(formula = formula, data = data, listw
= listw,
na.action = na.action, Durbin = Durbin, type = type, method =
method,
quiet = quiet, zero.policy = zero.policy, interval = interval,
```

```
tol.solve = tol.solve, trs = trs, control = control)

Residuals:
      Min        1Q    Median        3Q       Max
-0.577075 -0.133872  0.036026  0.192142  0.354781

Type: mixed
Coefficients: (asymptotic standard errors)
                  Estimate Std. Error z value Pr(>|z|)
(Intercept)      -0.652522   1.955511 -0.3337   0.7386
log(GDP2017)      0.022121   0.077920  0.2839   0.7765
lag.log(GDP2017)  0.090937   0.148207  0.6136   0.5395

Rho: 0.66505, LR test value: 13.855, p-value: 0.00019749
Asymptotic standard error: 0.13226
z-value: 5.0284, p-value: 4.9451e-07
Wald statistic: 25.285, p-value: 4.9451e-07

Log likelihood: -3.491194 for mixed model
ML residual variance (sigma squared): 0.062241, (sigma: 0.24948)
Number of observations: 37
Number of parameters estimated: 5
AIC: 16.982, (AIC for lm: 28.837)
LM test for residual autocorrelation
test value: 0.051563, p-value: 0.82037

> impact2<-impacts(model2,listw=W1)
Warning message:
Method impacts.sarlm moved to the spatialreg package
> impact2
Impact measures (mixed, exact):
Direct  Indirect     Total
log(GDP2017) 0.04775598 0.2897834 0.3375394
```

Spatial Error Models

```
model3<-errorsarlm(log(Unemp2017)~log(GDP2017),data=OL,listw=W1)
Warning message:
Function errorsarlm moved to the spatialreg package
>summary(model3)

Call:spatialreg::errorsarlm(formula = formula, data = data,
listw = listw,
na.action = na.action, Durbin = Durbin, etype = etype, method =
method,
quiet = quiet, zero.policy = zero.policy, interval = interval,
tol.solve = tol.solve, trs = trs, control = control)
```

```
Residuals:
      Min        1Q    Median        3Q       Max
-0.576705 -0.154990  0.080849  0.211270  0.338986

Type: error
Coefficients: (asymptotic standard errors)
             Estimate Std. Error z value Pr(>|z|)
(Intercept)  2.607737   1.167440  2.2337   0.0255
log(GDP2017) 0.026927   0.078091  0.3448   0.7302

Lambda: 0.67413, LR test value: 14.139, p-value: 0.00016981
Asymptotic standard error: 0.13042
z-value: 5.1687, p-value: 2.3569e-07
Wald statistic: 26.716, p-value: 2.3569e-07

Log likelihood: -3.802568 for error model
ML residual variance (sigma squared): 0.063015, (sigma: 0.25103)
Number of observations: 37
Number of parameters estimated: 4
AIC: 15.605, (AIC for lm: 27.744)

> impact3<-impacts(model3,listw=W1)
Error in spatialreg::impacts.sarlm(obj = obj, ..., tr = tr, R =
R, listw = listw,  :
impact measures not for error models
In addition: Warning message:
Method impacts.sarlm moved to the spatialreg package
> impact3
Error: object 'impact3' not found
> model4<-
GMerrorsar(log(Unemp2017)~log(GDP2017),data=OL,listw=W1)
Warning message:
Function GMerrorsar moved to the spatialreg package
>summary(model4)

Call:spatialreg::GMerrorsar(formula = formula, data = data,
listw = listw,
na.action = na.action, zero.policy = zero.policy, method =
method,
arnoldWied = arnoldWied, control = control, pars = pars,
scaleU = scaleU, verbose = verbose, legacy = legacy, se.lambda =
se.lambda,
returnHcov = returnHcov, pWOrder = pWOrder, tol.Hcov = tol.Hcov)

Residuals:
      Min        1Q    Median        3Q       Max
```

```
-0.822505 -0.200935  0.035146  0.214634  0.531002

Type: GM SAR estimator
Coefficients: (GM standard errors)
             Estimate Std. Error z value Pr(>|z|)
(Intercept)  2.581397   1.177140  2.1929  0.02831
log(GDP2017) 0.028480   0.078946  0.3607  0.71829

Lambda: 0.63417 (standard error): 0.35864 (z-value): 1.7683
Residual variance (sigma squared): 0.064672, (sigma: 0.25431)
GM argmin sigma squared: 0.064412
Number of observations: 37
Number of parameters estimated: 4
```

SARAR Models

```
Call:errorsarlm(formula = log(Unemp2017) ~ log(GDP2017), data =
> model5<-stsls(log(Unemp2017)~log(GDP2017),data=OL,listw=W1)
Warning message:
Function stsls moved to the spatialreg package
>summary(model5)

Call:spatialreg::stsls(formula = formula, data = data, listw =
listw,
zero.policy = zero.policy, na.action = na.action, robust =
robust,
    HC = HC, legacy = legacy, W2X = W2X)

Residuals:
      Min        1Q    Median        3Q       Max
-0.656803 -0.178604 -0.015311  0.127436  0.555784

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
Rho           1.458294   1.171920  1.2444   0.2134
(Intercept)  -1.658424   3.209978 -0.5166   0.6054
log(GDP2017)  0.020887   0.082979  0.2517   0.8013

Residual variance (sigma squared): 0.073416, (sigma: 0.27095)

> impact5<-impacts(model5,listw=W1)
Error in invIrW(listw, rho) :
  Rho 1.45829442822812 outside feasible range: -
1.56020380209393:0.999999999999999
In addition: Warning message:
Method impacts.stsls moved to the spatialreg package
> impact5
```

```
Error: object 'impact5' not found
> model6<-lagsarlm(log(Unemp2017)~log(GDP2017),data=OL,listw=W1)
Warning message:
Function lagsarlm moved to the spatialreg package
>summary(model6)

Call:spatialreg::lagsarlm(formula = formula, data = data, listw
= listw,
na.action = na.action, Durbin = Durbin, type = type, method =
method,
quiet = quiet, zero.policy = zero.policy, interval = interval,
tol.solve = tol.solve, trs = trs, control = control)

Residuals:
      Min        1Q    Median        3Q       Max
-0.567549 -0.146463  0.062137  0.208034  0.338727

Type: lag
Coefficients: (asymptotic standard errors)
             Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.353122   1.094200  0.3227   0.7469
log(GDP2017) 0.042581   0.070615  0.6030   0.5465

Rho: 0.67407, LR test value: 14.383, p-value: 0.00014916
Asymptotic standard error: 0.13005
z-value: 5.1833, p-value: 2.1802e-07
Wald statistic: 26.866, p-value: 2.1802e-07

Log likelihood: -3.6806 for lag model
ML residual variance (sigma squared): 0.062603, (sigma: 0.25021)
Number of observations: 37
Number of parameters estimated: 4
AIC: 15.361, (AIC for lm: 27.744)
LM test for residual autocorrelation
test value: 0.24181, p-value: 0.6229

> impact6<-impacts(model6,listw=W1)
Warning message:
Method impacts.sarlm moved to the spatialreg package
> impact6
Impact measures (lag, exact):
                Direct   Indirect     Total
log(GDP2017) 0.04974732 0.08089618 0.1306435
```

Appendix C

Analysis on Philip's Curve

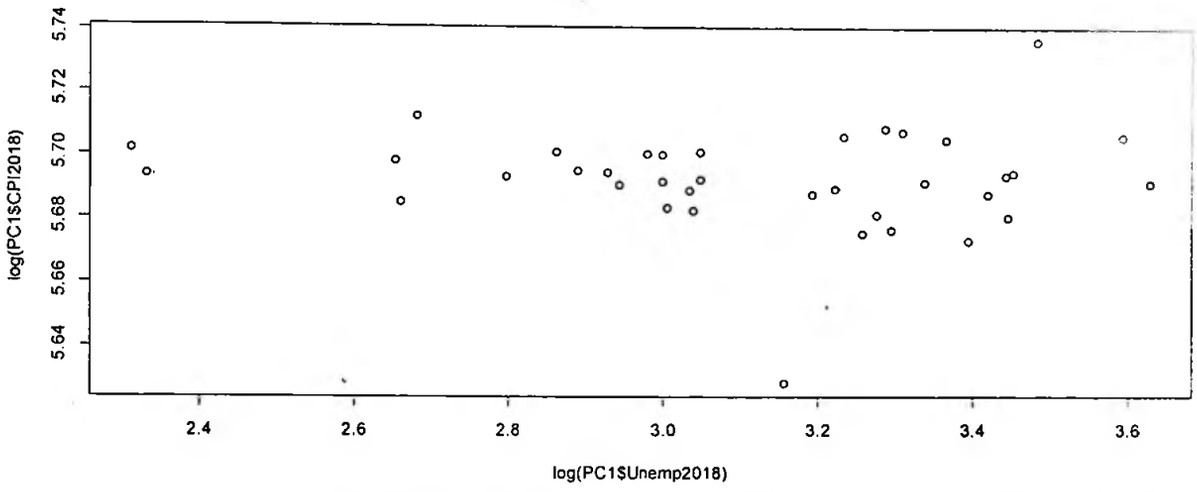


Fig 1: A Scatter plot of cross section of consumer price index against unemployment rate of states in Nigeria in 2018

```
> pc1reg<-lm(log(CPI2018)~log(Unemp2018),data=PC1)
>summary(pc1reg)

Call:
lm(formula = log(CPI2018) ~ log(Unemp2018), data = PC1)

Residuals:
      Min        1Q    Median        3Q       Max
-0.064145 -0.004760 -0.000208  0.007621  0.045036

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)     5.698528   0.026818 212.490   <2e-16 ***
log(Unemp2018) -0.001914   0.008582  -0.223    0.825
---
Signif.codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.0164 on 35 degrees of freedom
Multiple R-squared:  0.001419,  Adjusted R-squared:  -0.02711
F-statistic: 0.04975 on 1 and 35 DF,  p-value: 0.8248
```

```
dwtest(pc1reg)

        Durbin-Watson test

data:  pc1reg
DW = 1.5468, p-value = 0.06667
alternative hypothesis: true autocorrelation is greater than 0

bptest(pc1reg)

studentizedBreusch-Pagan test

data:  pc1reg
BP = 0.75203, df = 1, p-value = 0.3858


jarque.bera.test(pc1reg$residuals)

JarqueBera Test

data:  pc1reg$residuals
X-squared = 64.979, df = 2, p-value = 7.772e-15

lm.morantest(pc1reg,W1)

        Global Moran I for regression residuals

data:
model: lm(formula = log(CPI2018) ~ log(Unemp2018), data = PC1)
weights: W1

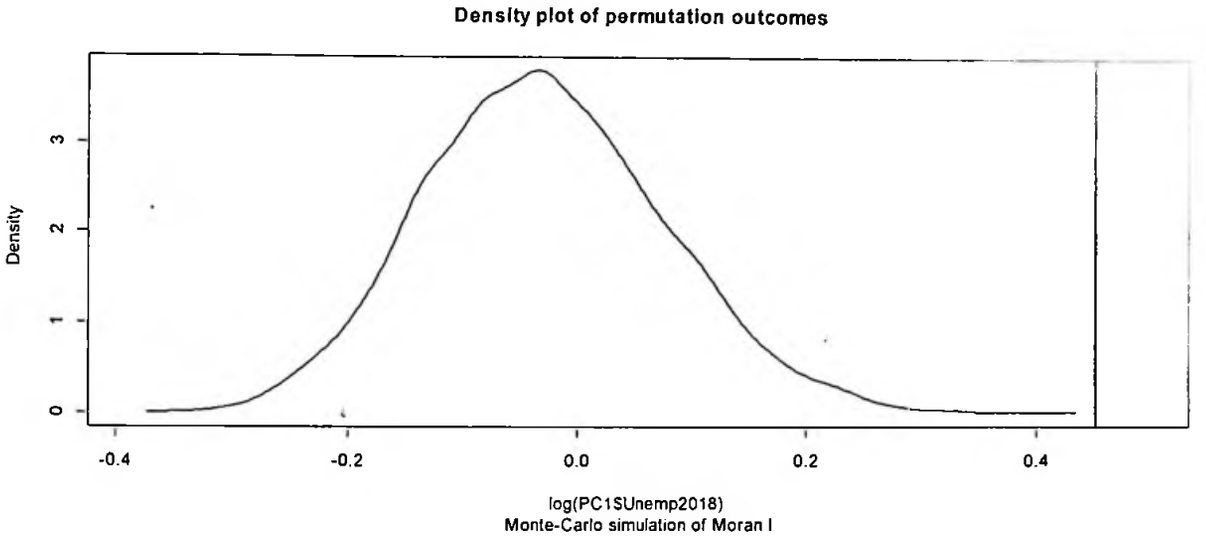
Moran I statistic standard deviate = 1.5704, p-value = 0.05816
alternative hypothesis: greater
sample estimates:
Observed Moran I      Expectation         Variance
      0.12029787      -0.04148979       0.01061387


MC<-moran.mc(log(PC1$Unemp2018),W1,nsim=10000)
> MC

        Monte-Carlo simulation of Moran I

data:  log(PC1$Unemp2018)
weights: W1
number of simulations + 1: 10001
```

```
statistic = 0.45214, observed rank = 10001, p-value = 9.9999e-05
alternative hypothesis: greater
```




```
LM<-lm.LMtests(pc1reg,W1,test="all")
>summary(LM)
summary(LM)
        Lagrange multiplier diagnostics for spatial dependence
data:
model: lm(formula = log(CPI2018) ~ log(Unemp2018), data = PC1)
weights: W1

statistic parameter p.value
LMerr    1.123479         1  0.2892
LMlag    1.131194         1  0.2875
RLMerr   0.014015         1  0.9058
RLMlag   0.021730         1  0.8828
SARMA    1.145209         2  0.5641

Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = log(CPI2018) ~ log(Unemp2018), data = PC1)
weights: W1

LMerr = 1.1235, df = 1, p-value = 0.2892


        Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = log(CPI2018) ~ log(Unemp2018), data = PC1)
```

```
weights: W1

LMlag = 1.1312, df = 1, p-value = 0.2875


        Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = log(CPI2018) ~ log(Unemp2018), data = PC1)
weights: W1

RLMerr = 0.014015, df = 1, p-value = 0.9058


        Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = log(CPI2018) ~ log(Unemp2018), data = PC1)
weights: W1

RLMlag = 0.02173, df = 1, p-value = 0.8828


        Lagrange multiplier diagnostics for spatial dependence

data:
model: lm(formula = log(CPI2018) ~ log(Unemp2018), data = PC1)
weights: W1

SARMA = 1.1452, df = 2, p-value = 0.5641
```

Spatial Lag Model for Philips Curve

```
model7<-lagsarlm(log(CPI2018)~log(Unemp2018),data=PC1,listw=W1)
Warning message:
Function lagsarlm moved to the spatialreg package
> model8<-
lagsarlm(log(CPI2018)~log(Unemp2018),data=PC1,listw=W1,type="mix
ed")
Warning message:
Function lagsarlm moved to the spatialreg package
>summary(model7)

Call:spatialreg::lagsarlm(formula = formula, data = data, listw
= listw,
na.action = na.action, Durbin = Durbin, type = type, method =
method,
```

```
quiet = quiet, zero.policy = zero.policy, interval = interval,
tol.solve = tol.solve, trs = trs, control = control)

Residuals:
       Min         1Q     Median         3Q        Max
-0.06362124 -0.00652829  0.00043486  0.00723159  0.04159534

Type: lag
Coefficients: (asymptotic standard errors)
                 Estimate Std. Error z value  Pr(>|z|)
(Intercept)     4.4107867  1.2294401  3.5876 0.0003337
log(Unemp2018) -0.0010572  0.0081836 -0.1292 0.8972157

Rho: 0.22576, LR test value: 1.0358, p-value: 0.30879
Asymptotic standard error: 0.21585
z-value: 1.0459, p-value: 0.29561
Wald statistic: 1.0939, p-value: 0.29561

Log likelihood: 101.1366 for lag model
ML residual variance (sigma squared): 0.00024446, (sigma:
0.015635)
Number of observations: 37
Number of parameters estimated: 4
AIC: -194.27, (AIC for lm: -195.24)
LM test for residual autocorrelation
test value: 0.27577, p-value: 0.59949

> impact7<-impacts(model7,listw=W1)
Warning message:
Method impacts.sarlm moved to the spatialreg package
> impact7
Impact measures (lag, exact):
                      Direct      Indirect        Total
log(Unemp2018) -0.001070019 -0.0002953878 -0.001365406
>summary(model8)

Call:spatialreg::lagsarlm(formula = formula, data = data, listw
= listw,
na.action = na.action, Durbin = Durbin, type = type, method =
method,
quiet = quiet, zero.policy = zero.policy, interval = interval,
tol.solve = tol.solve, trs = trs, control = control)

Residuals:
       Min         1Q     Median         3Q        Max
-0.06342954 -0.00649904  0.00050082  0.00742104  0.04178330
```

```
Type: mixed
Coefficients: (asymptotic standard errors)
Estimate  Std. Error z value  Pr(>|z|)
(Intercept)          4.41935929  1.23146309  3.5887 0.0003328
log(Unemp2018)      -0.00053465  0.01102503 -0.0485 0.9613225
lag.log(Unemp2018) -0.00116534  0.01634462 -0.0713 0.9431606

Rho: 0.2246, LR test value: 1.0192, p-value: 0.31272
Asymptotic standard error: 0.21601
z-value: 1.0397, p-value: 0.29846
Wald statistic: 1.0811, p-value: 0.29846

Log likelihood: 101.1391 for mixed model
ML residual variance (sigma squared): 0.00024446, (sigma:
0.015635)
Number of observations: 37
Number of parameters estimated: 5
AIC: -192.28, (AIC for lm: -193.26)
LM test for residual autocorrelation
test value: 0.39866, p-value: 0.52778

> impact8<-impacts(model8,listw=W1)
Warning message:
Method impacts.sarlm moved to the spatialreg package
> impact8
Impact measures (mixed, exact):
                        Direct     Indirect        Total
log(Unemp2018) -0.0006035272 -0.001588874 -0.002192401
```

Spatial Error Models for Phillips curve in Nigeria

```
> model9<-
errorsarlm(log(CPI2018)~log(Unemp2018),data=PC1,listw=W1)
Warning message:
Function errorsarlm moved to the spatialreg package
>summary(model9)

Call:spatialreg::errorsarlm(formula = formula, data = data,
listw = listw,
na.action = na.action, Durbin = Durbin, etype = etype, method =
method,
quiet = quiet, zero.policy = zero.policy, interval = interval,
tol.solve = tol.solve, trs = trs, control = control)

Residuals:
```

```
        Min          1Q      Median          3Q         Max
-0.06366570 -0.00654147  0.00043734  0.00724605  0.04152388

Type: error
Coefficients: (asymptotic standard errors)
                 Estimate Std. Error  z value Pr(>|z|)
(Intercept)     5.6960143  0.0283356 201.0201   <2e-16
log(Unemp2018) -0.0010782  0.0090423  -0.1192   0.9051

Lambda: 0.22594, LR test value: 1.0334, p-value: 0.30936
Asymptotic standard error: 0.21586
z-value: 1.0467, p-value: 0.29524
Wald statistic: 1.0956, p-value: 0.29524

Log likelihood: 101.1354 for error model
ML residual variance (sigma squared): 0.00024447, (sigma:
0.015636)
Number of observations: 37
Number of parameters estimated: 4
AIC: -194.27, (AIC for lm: -195.24)

> impact9<-impacts(model9,listw=W1)
Error in spatialreg::impacts.sarlm(obj = obj, ..., tr = tr, R =
R, listw = listw,  :
impact measures not for error models
In addition: Warning message:
Method impacts.sarlm moved to the spatialreg package
> impact9
Error: object 'impact9' not found
> model10<-
GMerrorsar(log(CPI2018)~log(Unemp2018),data=PC1,listw=W1)
Warning message:
Function GMerrorsar moved to the spatialreg package
>summary(model10)

Call:spatialreg::GMerrorsar(formula = formula, data = data,
listw = listw,
na.action = na.action, zero.policy = zero.policy, method =
method,     arnoldWied = arnoldWied, control = control, pars =
pars,
scaleU = scaleU, verbose = verbose, legacy = legacy, se.lambda =
se.lambda,
returnHcov = returnHcov, pWOrder = pWOrder, tol.Hcov = tol.Hcov)

Residuals:
        Min          1Q      Median          3Q         Max
-6.4261e-02 -4.9057e-03  5.0389e-05  7.8901e-03  4.4664e-02
```

```
Type: GM SAR estimator
Coefficients: (GM standard errors)
                 Estimate Std. Error  z value Pr(>|z|)
(Intercept)     5.6961714  0.0281859 202.0932   <2e-16
log(Unemp2018) -0.0011308  0.0089966  -0.1257      0.9

Lambda: 0.21202 (standard error): 0.50478 (z-value): 0.42002
Residual variance (sigma squared): 0.00024491, (sigma: 0.01565)
GM argmin sigma squared: 0.00024472
Number of observations: 37
Number of parameters estimated: 4

> impact10<-impacts(model10,listw=W1)
Error in spatialreg::impacts.gmsar(obj = obj, ..., n = n, tr =
tr, R = R,  :
obj$type == "SARAR" is not TRUE
In addition: Warning message:
Method impacts.gmsar moved to the spatialreg package
> impact10
```

SARAR Models for Phillips curve

```
> model11<-stsls(log(CPI2018)~log(Unemp2018),data=PC1,listw=W1)
Warning message:
Function stsls moved to the spatialreg package
>summary(model11)

Call:spatialreg::stsls(formula = formula, data = data, listw =
listw,
zero.policy = zero.policy, na.action = na.action, robust =
robust,     HC = HC, legacy = legacy, W2X = W2X)

Residuals:
      Min        1Q    Median        3Q       Max
-0.058666 -0.016466 -0.001917  0.012604  0.071387

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
Rho             2.3625413  3.0013969  0.7871   0.4312
(Intercept)    -7.7776370 17.1203057 -0.4543   0.6496
log(Unemp2018)  0.0070538  0.0170768  0.4131   0.6796

Residual variance (sigma squared): 0.00059083, (sigma: 0.024307)

> impact11<-impacts(model11,listw=W1)
Error in invIrW(listw, rho) :
```

```
  Rho 2.36254125643562 outside feasible range: -
1.56020380209393:0.999999999999999
In addition: Warning message:
Method impacts.stsls moved to the spatialreg package
> impact11
Error: object 'impact11' not found
> model12<-
lagsarlm(log(CPI2018)~log(Unemp2018),data=PC1,listw=W1)
Warning message:
Function lagsarlm moved to the spatialreg package
>summary(model12)

Call:spatialreg::lagsarlm(formula = formula, data = data, listw
= listw,
na.action = na.action, Durbin = Durbin, type = type, method =
method,
quiet = quiet, zero.policy = zero.policy, interval = interval1,
tol.solve = tol.solve, trs = trs, control = control)

Residuals:
        Min          1Q      Median          3Q         Max
-0.06362124 -0.00652829  0.00043486  0.00723159  0.04159534

Type: lag
Coefficients: (asymptotic standard errors)
                  Estimate Std. Error z value  Pr(>|z|)
(Intercept)     4.4107867  1.2294401  3.5876 0.0003337
log(Unemp2018) -0.0010572  0.0081836 -0.1292 0.8972157

Rho: 0.22576, LR test value: 1.0358, p-value: 0.30879
Asymptotic standard error: 0.21585
z-value: 1.0459, p-value: 0.29561
Wald statistic: 1.0939, p-value: 0.29561

Log likelihood: 101.1366 for lag model
ML residual variance (sigma squared): 0.00024446, (sigma:
0.015635)
Number of observations: 37
Number of parameters estimated: 4
AIC: -194.27, (AIC for lm: -195.24)
LM test for residual autocorrelation
test value: 0.27577, p-value: 0.59949

> impact12<-impacts(model2,listw=W1)
Warning message:
Method impacts.sarlm moved to the spatialreg package
> impact12
```

```
Impact measures (mixed, exact):
Direct  Indirect     Total
log(GDP2017) 0.04775598 0.2897834 0.3375394
```



```
Characteristics of weights list object:
Neighbour list object:
Number of regions: 37
Number of nonzero links: 172
Percentage nonzero weights: 12.56392
Average number of links: 4.648649

Weights style: W
Weights constants summary:
nnn S0       S1       S2
W 37 1369 37 17.63415 154.4067
```