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SPATIAL ANALYSIS OF POVERTY AMONG WOMEN IN GHANA

By

HARUNA ABDUL - KARIM

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Declaration

I hereby declare that this submission is my own work towards the award of MPhil. Degree and that, to the best of my knowledge, it contains no previously published materials by another person, nor material which has been accepted for the award of any other degree of the University, except where due acknowledgment has been made in the text.

<u>Haruna Abdul - Karim</u> ....

Student Signature Date

Certified by:

Dr. A.O. Adebanji ....

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Supervisor Signature Date

Certified by:

Prof. S.K Amponsah ....

____

Head of Department Signature Date

Dedication

This work is dedicated to my dear wife and children; Hekmat, Aakilah and Suabirina.

Abstract

In Ghana, although women constitute more than half of the total population, they are grossly disadvantaged in the sharing of political power, wealth, influence, employments etc. In some parts of the country, the well-being of women is highly affected by these inequities. This study used spatial econometric techniques to investigate the spatial distribution of poverty among women and explored the main factors that determine the incidence of women poverty in Ghana.This study draws on the 2008 GDHS household's women data with their wealth factor scores (economic status) as the response variable. PCA technique was employed to obtain 13 components from an initial 27 socio-economic, demographic and geographic variables. These were the regression variables in GeoDa. The results show a highly positive significant Moran's I (I= 0.396; p=0.001), indicating that neighboring areas have similar poverty status; that is poverty is a geographical phenomenon. Also, the poverty maps identified the three northern regions as the most endemic women poverty areas. The regression analysis further indicated that SLM [R^2 = 79.2%;Log.L=-234;AIC=498;SC=558] fit the data better than the SEM [R^2 = 79.0%;Log.L=-242;AIC=511;SC=568] and OLS [R^2 = 74.0% ;Log.L=-270;AIC=569;SC=630] models. The selection of SLM indicates that the rate of poverty of one area affects the poverty rates of its neighbors. The major significant determinants of women poverty in 2008 were the education related variables, parity, some occupational related variables and marital status (married). The variables that had no significant relationships with poverty are female headed household and couple married without living together.

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Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Background of Study

Poverty is a complex and multidimensional human phenomenon and is not only associated with income or consumption (considered as monetary), but with other factor such as gender equality, health, education, sanitation, water supply etc. (considered as non-monetary). The causes of poverty are many and its effects on the poor are overwhelming. Studies have shown that, factors greatly influencing poverty are not only economical but social, political, cultural, geographical, etc. (Spaho, 2014; Sen, 1999).

Poverty, in its fundamental sense, can be thought of as a deprivation or lack of basic physical needs such as food, shelter, health care and security, which are deemed necessary based on shared values of human dignity (Fapohunda, 2012). However, as Sen noted, necessity is not a uniform commodity and may vary across individuals, households and different societies, and needs may be relative to what is possible (Omideyi, 2008).

1.1.1 Key Definitions in the study

- Working poor: Those who are employed but live in household whose individual members are also employed but earned less than 1.25 Dollars a day.
- Vulnerable employment: It is the sum own account workers and contribut-

ing family workers and are not typically bound by formal work arrangements.

- Vulnerability: It is the probability that a person above the poverty line will fall into poverty in the future.
- Gender equality: Requires equal enjoyment by women and men to sociallyvalued opportunities, resources and rewards.
- Gender equity: it is the process of being fair to women and men.
- Incidence of Poverty (Head count Index): It is the segment of the population whose resource (income/consumption) is below the poverty line.
- Poverty line: It is the cut-off point separating poor from non-poor.
- Depth of Poverty (Poverty Gap): It provides information with regards to distance between the household and the poverty line. The estimate of PG gives the resources that are needed to pull all the victim of poverty (poor) to the poverty line.
- Multidimensional Poverty Index: Percentage of the population that is multidimensional poor adjusted by the intensity of the deprivations.
- Poverty Severity (Squared Poverty Gap): It provides information about how far a household is from the poverty line and also the inequality among the poor. This group represents the poorest of the poor. In multidimensional terms, it represents the percentage of the population whose deprivation score is 50% or above.

Generally, poverty can be expressed in two ways: Absolute and Relative poverty. Absolute poverty refers to living standards that do not meet standard specific minimum requirements, usually defined by a poverty line. For example, the World Bank definition of poverty is living on less than 1.25 Dollars per day.

Absolute poverty lines are often based on having adequate material resources to meet a person's basic human needs, such as having enough food and shelter to live independently (Fry and Chakraborty, 2014). Relative poverty refers to living standards that are deemed to be lower than other people in the population. For example; relative poverty could be defined as being one of the poorest twenty percent people in the population, or in other words having material living standards that are lower than eighty percent of the people in the population. Thus relative poverty is dependent on which population the person lives in. The wealth index is one way of determining relative poverty of a given population (Fry and Chakraborty, 2014).

The available literature on poverty (Sen, 2014) indicates that poverty was not a property of one sex, country or continent. Globally, the available statistics of poverty (UNDP, 2014) indicated that 1.2 billion people (22%) were extremely poor, that is they earned less than 1.25 Dollars a day and 1.5 billion people were multi - dimensionally poor (deprived of education, health, and living standards).

However, the gender disparities of poverty were over whelming, especially in the developing countries. For instance, it was generally established (UN, 1995; UNPD, 1996; Duncan, 2005; Fapohunda, 2012) that 70% of 1.2 billion people who earned less than 1.25 Dollars a day were women. According to Sen (2014) the non-gender view of poverty by policy makers and designers based on the premised that poverty affects both men and women equally was not only misleading but unacceptable. In many societies, Sen noted, women were deprived of ownership of assets, employment, and income and that the key to solving global poverty lies in targeting women and girls.

Fakuda (1999) opined that, using income to assess poverty has masked its significant effects on women. Women poverty, she noted, meant more than insufficient income necessary for material well being and that women poverty meant deprivation of all kinds. To her, the concept of poverty that truly reflects women poverty is 'Human Poverty' which she described as the deprivations of the opportunities and chances most basic to human life - the opportunity to live healthy, creative life and respect from others. She concluded that human poverty was more important than income poverty which was often used to describe women poverty. According to Deepa et al (2001), poverty is one of the leading causes of hunger, disease and even death in developing countries and that those who are greatly affected are women and children due to their disadvantage position in the society.

In sub - Saharan Africa (SSA), poverty is still one of the major obstacles to the economic development and growth in the region. Poverty in the region was very pervasive with 51% still living below 1.25 Dollars a day compared with an average of 27% of extreme poverty in other developing regions 1n 2009. Statistics has indicated that the trend of the proportion of income poverty and multidimensional poverty has been decreasing across all the regions except sub-Saharan Africa (SSA). For instance, the world was expected to meet MDG's 1a target of halving those who were extremely poor by 2015 as the present projections indicated that the world was on cause to reach 15% of the world's poor which was well below the initial target of 23%. However, in SSA, the trend was rather increasing (UNDP, 2010; UNDP, 2014).

McFerson (2013) noted that even though gender discrimination has brought about greater proportion of women suffering from extreme poverty worldwide, the situation in SSA was exacerbated by weak governance, violent civil conflict and traditional restriction of women to property right. He explained further that SSA was the only region where the entire three factors have combined to worsen women poverty. The extreme women poverty as well as severity and their vulnerability, was particularly marked in the region. The skilled birth attendance of 46% was the lowest among the developing regions with the highest maternal deaths of 470 per 100,000 in 2010 (UNDP, 2014). According to UN (2010a), some of the major reasons why SSA countries were finding it difficult to effectively reduce poverty in the region were failure to address women poverty, gender inequalities and some of the socio-cultural practices militating against women.

In Ghana, even though the overall national poverty profile was declining, the trend was not uniform across the length and breadth of the country. The country has witness a significant reduction in the incidence of poverty from 51% in 1990 to about 24.2% in 2013. However, the overall picture on declining levels of poverty masks significant gender disparities in some of the socio-economic and demographic indicators that were deemed to be strongly correlated with poverty. For instance, a high proportion of females (23.3%) have never been to school compared to males (14.6%) and that 67.3% of females can neither read nor write English as compared to 46% of males (GSS, 2014).

UNDP further noted that Ghana was largely on track in achieving the MDG 1 target at the national level and in rural and urban areas and noted however that the progress is fraught with gender inequalities and regional poverty disparities and these factors will hamper the achievement made over the years. The report lamented that the access of women to wage employment in non - agricultural sector has remained quite weak and this was undermining the country's quest to promoting gender equality and women empowerment. Moreover, the maternal mortality of 347 deaths per 100000 was unacceptable (UNDP, 2012; 2014). In light of the above disproportionate bias of poverty against women, gender activist across the world has been advocating since 1990s for the formulations of policies to address women poverty and gender inequalities by both national and international bodies. The first visible global policy designed to combat the menace of poverty were the UNDP yearly publications of Human Development Index (HDI) in 1990 and Gender Development Index (GDI) in 1995 to evaluate poverty and gender inequalities in all 189 member countries of United Nation (UN).These two indices were both constructed from the same indicators; education, health and living standards. These indicators, according to Sowunmi et al. (2012), strongly correlated with poverty.

Whiles HDI is a general index of the entire population; GDI is gender specific and reflect gender disparities in basic human capabilities. Since 2003 all Sub African countries, including Ghana, had ranked as the lowest in these indices, indicating the poor state of human development and gender inequalities in Sub - Saharan Africa (Sowunmi, 2012; UNDP, 2014).

The second international pro -poor policy formulated in 2000 by UN in collaboration with World Bank was the Millennium Development Goals (MDGs). The MDGs was duly signed by all 189 UN member countries as a millennium declaration in September 2000. The specific objectives of the MDGs, among others, were to eradicate extreme poverty and hunger, achieve universal primary education, promote gender equality and empower women, improve maternal health (GSS,
2013).

In the national context, the government over the years has designed various programs to address poverty and some of these programs include the Programme of Actions to Mitigate the Social Costs of Adjustment (PAMSCAD), Ghana Poverty Reduction Programme (GPRP I), Growth and Poverty Reduction Strategy (GPRS II), Likelihood Empowerment Against Poverty (LEAP), Ghana School
Feeding Programme (GSFP). National Youth Employment Programme (NYEP),

National Health Insurance Programme (NHIS) etc. (Sower, 2002; Sekyere, 2011). All the above pro - poor programs, except LEAP, fail to meet the intended set goals by targeting the core poor of the population. Each program covered less than 35% of the poor except LEAP (57%) (Sekyere,2011). Also, Bradshaw and Linneker (2003) noted that, most of the poverty reduction programs were failing mainly because they were not 'gendered sensitive documents' and most of them were tied to economic growth of various countries and that there were scanty evidence associating women poverty to economic growth.

Also, women were not fully integrated into the programs formulating and implementations stages and instances where they were included, their voices were generally ignored or marginalized, and their concerns about issues affecting them were treated as a secondary issue. What is clear from the above is that all the intended pro-poor programs were not achieving the desired results of targeting the core-poor of the population and two reasons could be attributed to their failures. Firstly, the designers failed to take into consideration the spatial distribution of poverty and this has resulted into poor targeting of the core-poor, especially poor women. Secondly, the geographical determinants of poverty were totally neglected and the designed programs were not getting the desired impact as they all mounted to putting squared pegs in around holes.

1.2 The Poverty of Profile of Ghana

1.2.1 Overview

Ghana has gone through almost four decades of pro-poor structural adjustments programs designed and implemented by various Governments, and despite all these efforts poverty in Ghana was still quite invasive. The most common instruments used to measure poverty in Ghana were the Census results and

Ghana Standard Living Surveys (GLSS) which were conducted by Ghana Statistical Service (GSS) in collaboration with other stakeholders such as the World Bank. The data from were systematically analyzed and report which contain the poverty state of the country was published by GSS (Sower, 2002).

GSS (2013) reported that the overall national Multidimensional Poverty Index (MPI) incidence is 42.7%. This figure was higher than the national income poverty measure of 24.3% reported in the GLSS 6 by GSS in 2014. The MPI results also highlighted the regional and locational (urban and rural) disparities in poverty. Greater Accra was the least poor region whiles the three northern regions were the poorest regions in the MPI poverty incidence. The results were summarized in the table 1.1 below. Also, except Greater Accra region, all the rural areas in the nine regions were Multidimensional poor and contribute an average of 72.3% to the overall national MPI poverty incidence.

(GSS, 2013)

Region	% of MPI Poverty: Head Count Ratio (H)	% by Localities:	
		Urban	Rural
Ghana	42.7	27.7	72.3
Gt. Accra	18.5	79.1	20.7
Ashanti	30.8	38.2	61.8
Eastern	35.6	24.1	75.9
Central	39	36.5	63.5
Western	40.5	23.0	77.0
Volta	42.2	20.7	79.3
B/Ahafo	51.7	28.4	71.6
U/West	77.6	7.4	71.6
U/East	80.8	12.7	87.3
Northern	80.9	19.2	80.8

The analysis of the results of the indicators used in the construction of MPI poverty indicated that education of household members and standard of living were the largest contributors to overall poverty in Ghana at both rural and urban areas.

1.3 Problem Statement

Several studies on poverty in Ghana [and other places] (World Bank, 2011; GSS, 2013) clearly indicated that the distribution of poverty in the country was nonuniform. There were remarkable large regional/locational disparities of poverty.

The regional disparities of poverty in space could be attributed to the operations of socioeconomic, geographical, demographic or political factors working in space to divide the country into areas of low poverty rates and other areas of high poverty rates (Voss, 2006).

This indicates that poverty rates in neighboring areas were probable similar to one another, hence the need to pay attention to the structure of the autocorrelation (Spatial dependence) in our data. Ignoring this can results in inconsistent or biased estimates of the actual impact of the determinants of poverty (independent variables), especially when OLS is employ as the method of estimation (Yrigoyen, 2008; Minot et al., 2003).

Sowunmi et al (2012), applied spatial techniques on National Living Standard Survey and Core Welfare Indicators Questionnaire Survey to explore the presence of spatial auto correlation in the Nigeria's Senatorial Districts and the results revealed a positively significant spatial autocorrelation but no attempt was made to fit appropriate model for the data. Also, Adebanji et al. (2008) and Higazi et al. (2013) both used spatial techniques to fit appropriate models to determine the possible causes of poverty in Somalia and Egypt respectively. But the proxy indicator employed to identify the poor was monetary and also, their studies were non-gender based. In Ghana, however, even though several studies on poverty (Ennin et al., 2013; Agyeman et al., 2012) were done, no effort was made to far to explore the existence of spatial dependence in the poverty data, let alone using spatial econometric techniques to explore the key determinants of poverty.

This study therefore intends to use spatial econometric techniques to explore the existence of or otherwise of spatial autocorrelation in WFS of 2008 GDHS (which is non-monetary indicator) and fit appropriate spatial model to determine the possible causes of women poverty (gender based) in Ghana.

1.4 Research Questions

- Where are the hotspots and coldspots of the incidence of poverty among women in Ghana?
- Are the identified areas poverty traps?
- Do we have feminization of poverty in Ghana?
- Why are there places in Ghana where women are persistently poor?
- Can we model the characteristics of places that experience a lot of women poverty in Ghana?

1.5 Research Objectives

1.5.1 General Objectives

The main objectives of this research is to use spatial techniques to investigate the main factors that determine the incidence of women poverty in Ghana using 2008 GDHS data.

- To use spatial regression to explore the incidence of women poverty in Ghana using clustered wealth factor scores of 2008 GDHS data

- To determine the spatial Autocorrelation that exists in the wealth factor scores of women.
- To fit and interpret a Spatial Error or Spatial Lag regression model to assess the spatial nature of WFS of women and their neighbors.

1.6 Scope and Limitation

This study employed secondary data of 2008 GDHS data. Even though modeling poverty using administrative data such as DHS are having advantages of broad temporal and spatial coverage, low marginal cost, accuracy, automatic collection and storage, it is however fraught with the constrain such as the data not primarily designed for modeling. Also, another major limitation is the lack of information on income and expenditure of the households for comparative analysis. This would have added more in-depth information on the state of women poverty in Ghana.

1.7 Methodology

1.7.1 Sampling Techniques

A nationally representative secondary data derived from Phase IV of Ghana Demographic Health Survey (GDHS) conducted by Ghana Statistical Service (GSS) and Ghana Health Service in 2008 was used for this study. The study area is the entire country, while the study population is all the householdsaˆ women in the survey/sample. In 2008, for the households selected for individual interview in the survey, a total of 5,096 eligible women (15 to 49 years) were identified; interviews were completed on 4,916 of these women, yielding a response rate of 97 percent (GSS, 2008).

The wealth quintile, as constructed, used information on household ownership of consumer items, ranging from a television to a bicycle or car, as well as dwelling characteristics, such as source of drinking water, sanitation facilities, and type of flooring material.Each asset was assigned a weight (factor score) generated through principal components analysis, and the resulting asset scores were standardized in relation to a normal distribution with a mean of zero and standard deviation of one.

Each household was then assigned a score for each asset, and the scores were summed for each household; individuals were ranked according to the total score of the household in which they resided. The sample was then divided into quintiles from one (lowest) to five (highest). A single asset index was developed for the whole sample; separate indices were not prepared for the urban and rural populations (GSS, 2008).

The five wealth quintile groups are:

1. The poorest 20% of the sampled population, i.e.0% ≤ y_i ≤ 20% category belonging to the lowest quintile.

2. The next poorest 20% households, i.e. 21% ≤ y_i ≤ 40% category, belonging to a group which is richer than the lowest quintile but poorer than the other three quintiles.

3. Households within the 41% ≤ y_i ≤ 60% category, belonging to a group which is richer than the two lowest quintiles but poorer than the top two quintiles.

4. Households within the 61% ≤ y_i ≤ 80% category, which is a group directly below the richest quintile.

5. The highest quintile made up of the richest 81% ≤ y_i ≤ 100% of households.

Where y_i represent the wealth factor scores of the household.

1.7.2 Statistical Methods

One of the objectives of spatial statistics is to characterise spatial patterns in the data, when the data is spatially auto correlated or dependent. The dependency of the spatial structure in the poverty data over space excludes the utilization of many traditional statistical models such as OLS that require independence between observed measures as a fundamental attribute. According to Anselin (1992), the spatial patterns can cause problems such as spatial dependence and heterogeneity, which make the traditional methods such as OLS invalid. These problems can be identified and quantified by spatial statistics through the use of exploratory and confirmatory analysis tools, ESDA and CSDA, respectively. ESDA is used to visualize and describe spatial distribution of women poverty and whiles CSDA is use for quantitative processes modeling, estimation and validation of the spatial components in the data (Lopes et al, 2010).

1. Spatial autocorrelation (Moran's I): It uses Moran's I Index to indicate,through values that vary from -1 to +1, how similar each region is to its immediate neighbor. The closer to zero, the less the spatial autocorrelation. Values close to -1 or +1 indicate the presence of negative or positive autocorrelation. As such, Moran's I is very useful for the analysis of the initial stage of poverty modeling, allowing the identification of characteristic of the dependent variable and possible independent variables.

2. The Moran Scatter plot: it is constructed using normalized values of theanalysis variable (y), which are compared with the average of the neighborhood values (Wy) in a two dimensional graph divided into four quadrants. The quadrant indicate points of positive spatial association, signifying that a local has neighbors with similar values also known as

spatial clusters (Q1 and Q3) or indicate points of negative spatial association, signifying that a local has neighbors with distinct values, also known as spatial outliers (Q2 and Q4).

3. Local Moran's Index: provide a unique value as a measure of spatial association for the grouping of data; the local indicators produce a specific value for each area, allowing the identification of regions with similar attribute values (clusters), with outliers, and with more than a spatial regime.

   Anselin (1996) refers to the local indicators as LISA (Local Indicators of Spatial Association) statistics.

Unlike the traditional methods, spatial models employed additional parameter called shift parameter to the traditional methods to account for the spatial structure in our sample data. Two of the spatial regression methods employed in this study were the Spatial Lag Model (SLM) and Spatial Error Model (SLM). SLM is used to account for the effect due to the influence from neighboring weighted average of the dependent variable and SEM is used to account for the effect due to the correlation among the residuals.

Chapter 2

Literature Review

2.1 Introduction

This chapter focuses on the available literature on poverty and generally grouped in the following sub-section; some selected key definition in the study, concept and measurements of poverty, overview of poverty which looks at the related studies and strategies to tackled poverty.

2.2 Concept and Measurements of poverty

Poverty refers to a situation in which an individual, household or grouped of people have low economic status (standard of living) and also deprived of their right to a minimum level of resources (Atkinson, 1987). Conceptualization poverty this way, according to literature, is helpful from the perspective of accepting and tackling women poverty. There are two main approaches or indicators used in measuring poverty; monetary indicators and non-monetary indicators. Poverty analyst using monetary indicators in estimating poverty will have to make a decision between income and consumption as the appropriate indicator to quantified the well-being of the unit of analysis [individual, household, or family] (Maliki,
2011). The approach adapted, to some extent, depends on the unit of analysis (Atkinson, 1987).

For non-monetary indicators, studies have revealed that poverty is highly correlated with unsatisfactory (insufficient) outcomes with respect to health, education, literacy, nutrition, low self - esteem etc. These were important dimensions of human capabilities and can broadly be grouped (but not limited to) in to: health and nutrition poverty, education poverty, and composite index poverty (Woden, 2008). As Sen put it, the two indicators have to be properly integrated into the broader and fuller picture of success and deprivation of the unit of analysis (Atkinson, 2003).

The next logical step after selecting the indicator to be used is to choose an appropriate poverty line. This is the threshold or cut off point separating the poor from non-poor. The two commonly cutoff points are the Absolute poverty Line (APL) and Relative Poverty Line (RPL). RPL is defined in reference to the total income or consumption distribution in a given country. For example APL could be set as 40% of the average consumption of the country (PSI, 2010). APL on the other reflect the basic needs of a household, in other words, it is the lack of sufficient income to meet the basic physical needs of household or individual. APL anchored on basic 'survival' needs necessary for production and reproduction. The important thing to note is that, unlike RPL, APL reflects the actual needs of the victim of poverty and not by reference to the consumptions of those who are not living in poverty. In developing country like Ghana where majority of the population are barely surviving with minimum income, APL often proves to be more effective and relevant (Woden et al., 2008).

Finally, a mathematical relation will now be employed to convert the collected household characteristics or information with respect to a poverty line into a single value to represent poverty rates of the population as a whole. The three commonly measures are Incidence of Poverty, (Head count Index), Depth of Poverty (Poverty Gap) and Poverty Severity (Squared Poverty Gap).

2.3 Overview of Women Poverty

The recent global statistics on poverty has indicated that about 1.2 billion people live on less than 1.25 Dollars per day (income poverty), and 2.7 billion live on less than 2.50 Dollars per day in 2012. For multidimensional poverty, 1.5 billion people are poor, an estimated further 0.8 billion people live in a situation described as near-poverty in 2012 (Stiglitz and Kaldor, 2013). Even though the numbers were declining, many people were however living near the boundaries of both income and multidimensional poverty and they have the highest likelihood of falling into poverty with any economic shocks or recession (UN Global Pulse, 2012; UNDP, 2014).

Survey and data showed that even though poverty was a global phenomenon which affects the life of millions of people all over the world, it rather affected women more than men. This situation was compounded by social inequalities which were evidence in both developed and less developed countries. Most countries lack legal framework to address the specific needs of women and this has made them vulnerable to natural disasters and economic doldrums. For instance, the recent economic recessions which started somewhere 2008 has affected women the most, in France for example, women experienced unemployment rate of 8.5% higher compared to 7.4% of men as a result of the economic recession and this estimate has even excluded the large number of women engaged in precarious jobs, these unemployed women were all vulnerable to poverty (UN, 2010a). ITU (2013) further noted that economic recession was strongly related (associated) with fivefold increase of infant female mortality compared with male infant mor-
tality.

The phenomenon of gender unemployment inequalities was worrisome even in the most economically advance countries such as USA, the inequalities was very pervasive. Statistics has indicated that in 2009 the unemployment rate of women in USA were 13% higher and this has resulted in millions of them picking up arms and match into battle with poverty. Also, the gender wage gap in USA was overwhelming, and this was very surprising indeed, considering the fact that the country's "Equal Pay Act"came into existence more than five decades ago (UN, 2010c).

In the global perspective, the picture was even more alarming. In 2009 a significant number of 6.3% of female labor force were unemployed compared with 5.9% of male and this trend was consistent for several decades (UN, 2010c). This gender unemployment inequality was one of the major contributory factors of "feminization of poverty "[female headed households dominating over male headed household in poverty] (UN, 2010b).

According to (UN, 2010b), poverty feminization was highly correlated with child poverty, thereby depriving children of their well-being. Statistics had shown that these children will grew up with many deficiencies such as negative health outcome, poor nutrition, mental retardation, low educational attainments, and early death. They were equally vulnerable to adult poverty in the future and the cycle of poverty continues (UNDP. 2014).

According to 2014 UNDP annual report on Human Development Index (HDI), despite all the legal framework in most countries' statuary books, the discriminations against women were still very pervasive, especially in the areas of family matters, marriage, economic right and violence. The findings of a study conducted by Krutikova (2010) showed that in the countries where there were pervasive institutional discrimination against women, the primary school completion were 15% lower, the rate of children under nourishment and maternal mortality were twice higher. Another study conducted by Friedman and Schady (2009) also indicated that, in the countries where women lack control over their social and economic rights, maternal mortality was 85% higher, and in countries where women did not have the right ownership to land, the number of under nourish children were 60% higher.

Elaborating on women poverty and some of the discriminatory practices against women, UN (2010a) attributed this to lack of women in key decision making bodies of matters affecting them, particularly the phenomenon of "missing women "in politics. For instance, in most countries, even though women were free to participate in political activities, their numbers in parliament was not matching their share of the population. Only Rwanda (61%) and Cuba had proportion of female parliamentarians that match or exceeded their share in the population.

For the 60 countries surveyed in 2012, there were only 20% of female parliamentarians (UNDP, 2014). On the subject of gender income inequalities, the Project Concern International, an International NGO working towards eradication of poverty among women, observed that even though women work two thirds of the world's working hours, they earn only ten percent (10%) of the world's income and own less than one percent (1%) of the world's property.

In Sub-Saharan Africa (SSA), poverty phenomenon was very gloomy and the region was deemed as poverty endemic region among all the six regions in the world (UN, 2010a; UNDP, 2014). The 2004 ILO report on global poverty trend has indicated that whiles the global numbers of those who were living on less than 1 Dollar per day has reduced considerable from 1.45 billion to 1.1 billion for the past two decades, the numbers in SSA rather increased from 164 million to 314 million. This number included some 155 million women and men of working age (Fapohunda, 2012). According to UNDP 2014 report on 40 SSA countries, income poverty and multidimensional poverty were 50.9% and 59.6% respectively. Also, the intensity of deprivation and near - multidimensional poverty were55.0% and 16.2% respectively.

The World Bank report has indicated that all the regions were on track in the progress towards achieving MDG 1a target of halving the extreme poverty by 2015 except SSA. UNDP (2014) further stated that the picture was even scaring as majority of households were just at the threshold of both income and multidimensional poverty and were equally vulnerable to poverty. SSA accounted for more than 50% of world's working poor and vulnerable employments. And this was largely attributed to gender inequalities and social discrimination against women in the region (UN, 2010c). Given that, it is not surprising that SSA has the worst average regional score of Gender Inequality Index of 0.578 against the world average of 0.451 in 2014 UNDP annual reports.

Studies (Mariama, 1992; Babatunde et al., 2008) showed that women in the region contributed about 60 to 80% of agricultural production, in addition to their traditional roles as mothers and home keepers and yet their effort appeared to be invisible to the larger society simple because women were regarded as subordinate to men. Collaborating on the same subject, McFerson (2013) explained that, SSA women were the bed rock of food production in the region with 90% of hoeing, under taking 60% of harvesting and marketing and 80% of storage and processing, yet the restriction of the property right has made them owned less than 10% of their farm lands and this has made them economically vulnerable to poverty. Peterman et al. (2010) in a study to investigate the gender gap in agriculture in Nigeria and Uganda using multivariate Tobit model, indicated that education, age and other social cultural practices were significantly contributed to the low production among female headed household and female-owned plot
farmers.

In the study entitled “Poverty Among Women in SSA: Review of Selected Issues ”, McFerson (2013) explained that, to understand SSA women poverty, distinction need to be made between Structural poverty and Contingent poverty. Whiles Contingent poverty is trigged by a specific adverse effect such as instant changes in fuel prices, and therefore temporal in nature, structural poverty, by contrast, is deeply rooted in the socio-economic, political and cultural practices and rooted in the fabrics of society or a nation. According to him SSA woman were living in structural poverty and this does not easily eradicated with social policies. This poverty, he explained, was the worse form of poverty because it was a combined aspect of income poverty, asset poverty, opportunities poverty, and access poverty, and this has literally made SSA women ’poorest among the poorest’.

In a world Bank sponsored study of ’Time Use and Poverty’ of SSA women conducted by Blackden and Woden in 2006, the results indicated that ’Time Poverty’ worsen both income and asset poverty. They explained that, multitask nature of SSA women has compelled them to spent more time on non-marketable activities than economically productive activities. Time also limited them to expand their capabilities in education and skill training programs to enhance their opportunities in the labor market, and add value to their products. Moreover, time impedes on the girl child education due to the additional household tasks.

The total picture of women poverty was eluding the continent mainly because the income approach adopted by most countries to measure women poverty was masking the gravity of the situation in the region (Fakuda, 2012). For instance, a study conducted in Guinea in 1998 has indicated that there was no significant difference of the extreme poverty between male headed households and female headed households, however, other methods, such as community participatory approach, employed on the same subjects revealed a female headed households were worse off result (Fakuda, 1999).

Maternal mortality was still a major challenge in SSA with the region and Southern Asia accounting for about 87% of the global maternal mortality in 2008. Skill birth attendance at 46 percent in SSA was the lowest among all the six regions and this largely gave explanations as the highest maternal deaths in the region at 640 in 2008 and 474 in 2010 per 100,000 live births and some countries in the region such as Sierra Leone even recorded as high as 890 maternal deaths per 100, 000 in 2010 (UNDP, 2012; UNDP, 2014). Most of the maternal deaths occurred in the rural areas of SSA as a result of inadequate transport infrastructures and immobile nature of the roads in the rural areas to the nearest health centers (Porta, 2010).

Linking the high maternal mortality to high fertility rate in the region, a study has shown that the high incidence rate of some diseases such as malaria claimed about 300 to 500 million deaths of children annually, and this has contributed to mothers giving birth to more children to off-set the lost. The consequences were that, the high fertilities constrained mothers' employment opportunities, because child rearing took up most of their time, and mothers, especially from poor families, were economically worse off, resulting in them falling in to poverty (Sachs, 2001).

According to UNAIDS, SSA accounted for67% of the global HIV/AIDS infection in 2007 and that women were disproportionally more affected than men (Kalipeni and Zulu, 2010). The societal and cultural factors in the region made more women vulnerable to HIV/AIDS pandemic which has claimed the life of many mothers. According to UN (2010a), recent data of the disease in SSA has indicated that the proportion of female infected with HIV/AIDS was on the rise and that female accounted for more than 50% of the total HIV cases in the region in 2009. Most women in the region have little control over their sex life and this has made them more vulnerable to the HIV pandemic (Kalipeni and Zulu, 2010).

Like the rest of the world, SSA were not exempted from the effects of the 2008 to 2009 world financial, food and fuel crisis, however , females were the noticeable victims. SSA has recorded an overwhelming excess of about 30,000 to 50,000 infant mortality due to global economic recession (Friedman and Schady, 2009). Using a series of spline regression on DHS and other surveys, the results revealed that a 1% decreased in the GDP of SSA resulted in an increased infant mortality of 0.25 per 1,000 boys, but this has remarkable increased to about 0.90 per 1,000 infant mortality of girls. One possible explanation to this stacked differences was that, households in the region may gave more security to boys than girls when their income falls (Friedman and Schady, 2009).

In Ghana, the available statistics on poverty in 2012 has indicated that 30.4% and 28.59% of Ghanaians were living in multidimensional headcount poverty and income poverty respectively. Also, severity and intensity of poverty were 15.4% and 47.7% respectively. Though the figures were comparatively lower in the SSA region, the 47.7% of those living in intensity of poverty clearly suggested that the situation was not stable since all these people were equally vulnerable to poverty with the slightest economic shot falls (UNDP, 2014).

Recent studies (GSS, 2014; UNDP, 2012) have indicated that poverty rates in the country were declining and that the country was on track to achieving MDG 1a target by 2015. However, UNDP (2012), noted that poverty was more than just income poverty and that the correlates of poverty in the country will derail the country's effort in achieving the income poverty of halving those earning less than 1.25 Dollars a day by 2015. The report was particularly concern about other social

inequalities, especially with regard to maternal mortality, lack of women in key decision making bodies such as parliament and high poverty rates in some parts of the county. According to UNDP (2014), even though women were more than 50% of the total population, this has failed to translate into parliamentary presentation and labor force participation where women respectively recorded 10.9% and 67.2% compared with 89.1% and 71.2% of male.
Like the other parts of SSA, poverty in Ghana also has a strong gender dimensions. Studies had shown that women predominant among the core poor in the country (Sekyere, 2011). In relation to women povert, the GPRS defines poverty as "unacceptable physiological and social deprivation exacerbated by among other factors the lack of capacity of the poor to influence social process, public policy choices and resource allocation and the disadvantage position of women in society "(Duncan, 2004).

According to 2014 UNDP report, Ghana's HDI was depreciated by 1 from 2012 and still rank 138 out of 187 countries and with the same ranking in GII, indicating poor performance in both human development and gender inequalities in the country. Also, Gini coefficient, which measures the distribution of income among individuals or household within a country from a perfectly equal distribution, was worsening, indicating high income inequalities.

The maternal mortality is still worrisome at 350 per 100, 000 in 2012. Even within women, significant disparities exist, for instance, 94% of births by women from the richest quintile were attended by skilled service providers whereas the figure drops to 24% for the poorest quintile. Also, about 45.7% and 21% of sick pregnant women in the Northern and other regions were respectively unable to attend health facilities due to distance from the health facilities in 2010 (MDBS, 2012).

FAO (2012), explained that rural Ghanaian women engaged in agriculture were generally poorer due to high cost of agricultural input and low cost of agricultural product. The report further indicated that rural women were migrating to the urban centers to search for non - existing jobs because they cannot make living out of their efforts in agriculture.

According to Wrigley - Asante (2008), who conducted a study in the Dangme West District of Ghana women in Ghana were generally poorer than their men counterparts and income inequalities was evidence in all aspect of the economy. In a separate study in 2011, the same author indicated that Ghana traditional family structure has yielded unconditional control over household resources and decision making to the husband and their wives were largely relegated to the background and this has made most women lost their economic status and voice in the family matters, even on matters affecting them.

This results was collaborated by Gbedemah et al. (2010) who noted that Ghanaian women were less likely to utilize the productive resources to better their lots. A majority of female-headed households, according to them, (61% of urban and 53% of rural) fall into the poorest quintile of the population, and this number has increased from around 25.7% in 1960 to over 33% in 2008.

2.4 Evaluative Strategies to Tackle Poverty Using Spatial Techniques

Poverty is a complex social phenomenon and its possible causes are diverse as its sufferers. The complex nature of poverty has drawn the attention from researchers and non-researchers all over the world. Some current studies on poverty (Voss et al., 2006) were based on the hypothesis that households with similar characteristics sometimes were found close to one another either by choice or as a result of some external socioeconomic, geographic or political factors that constrain then to relocate.

The modern advancement of spatial econometrics techniques has made it possible not only to identify these households but to quantified the spatial pattern of poverty (concentration of poverty/spatial clusters and spatial outliers) (Anselin, 2001). According to Anselin (2002) and Minot and Baulch (2003), the rate of poverty in neighboring communities were likely going to be similar or error generated from the model in one community will be correlated with the error term in the neighboring communities; hence the need to account for spatial dependence or autocorrelation in the data with geographical components to eliminate this correlation. If spatial dependence is ignored, it will be:

- More difficult to explain any possible variation in the incidence of poverty across clusters.
- Impossible to quantified spatial outliers and concentration of poverty.

Studies have shown that knowing exactly where the "hotspots "of poverty exist will aid policy designers, researchers and other interest groups in making evidence base decision of targeting the poor and the effective implementations of pro - poor policies and programs (Adebanji et al., 2008; Minot et al, 2006).

As to why we have non-uniform distribution of poverty across different geographical location of the same country or continent, Voss el al. (2006) clearly explained that there were operations of socioeconomic, geographic or political factors working in space to partition countries and regions into large areas of high poverty and large areas of low poverty. Adam Smith, the famous Scottish economist, also made a strong hypothesis on the subject by suggesting that the physical Geography of the region can influence its poverty status. He contended that the coastal areas which are located near waterways experience favorable economic condition than the tropical climatic regions (Sachs, 2001).

Holt (2008) used spatial analysis techniques to explore the Topography of poverty in the United States of America (USA) findings indicated that about 52% percent of the 3,139 counties were classified as having similar spatial clusters or concentrations of poverty (LL and HH), with only about 8% classified as spatial outliers and the remaining 40% were neither spatial outliers nor spatial clusters. As Voss et al. (2006) noted, the classification of spatial clusters into high or low poverty rates is in line with average national poverty rates. In USA, the counties were located in the LL and HH sub regions. That is, counties with the rate of poverty above (below) the average poverty rate were neighbors of counties whose poverty rates were above (below) the average national poverty rates.

Another related spatial approach to explore the determinants of poverty in USA, Rupasinghe and Goetz (2007) found a significant spatial autocorrelation in the response variable (rate of poverty) which indicates that the poverty rates in neighborhood counties were similar. The coefficient of spatial autocorrelation was found to be 0.2. They interpreted this positive significant coefficient as a 10% point increase in the rate of poverty in a given county resulted in approximately a 2% increase in nearby counties' poverty rates. Also, the positive spatial autocorrelation highlights strong evidence of spillover or diffusion effect between counties with respect to poverty in USA. This was elaborated further by Crandall and Weber (2004) who stated that the poverty rate of a county is tied to the fortunes of their neighbors and as such the reduction of poverty of the neighbours affects the count's poverty rates.

Torres et al. (2010) explored the pattern of rural poverty in Sao Francisco River Basin in Brazil with Moran's I statistic and cluster maps to locate the "coldspots

”and “hotspots ”of poverty in the Basin using the Municipalities level data on rural poverty in 2003. The results showed that Moran’s I for all the Municipalities was 0.72, strongly suggesting a positive spatial dependence of rural poverty in 2003. The positive spatial dependence implies that for the rural Basin, that there were more municipalities with low (high) rural poverty surrounded by municipalities with the same low (high) rural poverty than would be the case that one would have been expected if poverty were randomly distributed.

Also, the rates of poverty of the Basin were positively spatially correlated for 90% with 42% LL and 48% HH. For the 42% LL, it implies that 42% have below - average poverty rates and were surrounded by municipalities of the same below - average poverty rates. One remarkable feature showed in the paper was that different weighing matrices, though all indicated consistent pattern of rural poverty, produced different Moran I: [**Queen**(I = 0.721); **Euclidean** distance (0.652); **Threshold distance** (0.651); **k -Neighbors** (0.685)].

It is interesting to note that spatial analysis can also be used to determine spatial dependence of poverty in several countries in the world. For instance, Samet et al., (2010) applied spatial analysis techniques to determine the spatial dependence of poverty in 43 Arab and Moslem countries in 1975 and 2000 using their per capita income.The results and showed a positively significant spatial dependence coefficient for the two years (1975: Moran’s I = 0.51, p - value = 0000; 2000: Moran’s I = 0.61, p - value=0.000).These findings indicated that if a country neighbor is poor, there will be a negative regional effect on its income, and vice versa. A study was conducted in Nigeria to explore the landscape of poverty in the countryˆas 109 Senatorial Districts, and the results showed a positively significant spatial autocorrelation (I=0.126, p-value=0.001). Both simple LMs were significant (at 5%) [LMLag value=11.667, p - value=0.001; LM err = 4.026, p value=0.0447] but only the robust LMLag was significant [Robust LMLag=7.651, p - value=0.0057; Robust LM err=0.0003, p - value=0.9867]. The result indicated a strong evidence in support of lag dependence and suggests that the incidence of poverty in a Senatorial District was influence by the incidence of poverty in the neighboring Senatorial Districts (Sowunmi et al., 2012).

Spatial analysis techniques are not only employ to detect the existence or nonexistence of spatial dependencies of poverty over space but more importantly, it can also be used to determine the possible causes of poverty over space using appropriate spatial econometric models.And it is not surprising that these techniques are fast becoming common tools for determining the major causes of poverty, especially in developing countries due to their advantages of simultaneously targeting the poor and also determining the causes of poverty.

Adebanji et al. (2008) conducted a study in Somalia by applying one of the spatial econometric models called Spatial Durbin Model (SDM) to determine the possible causes of poverty in the Bari regions using a household's inability to afford two square meals a day as an indicator to identifythe poor households. The finding from this study showed that Satellite settlements will be 10% more likely to be poor than communities located in the independent settlements and also communities whose main occupation were pastoral and fishing will be 20% more likely to be poor than farming communities.

In a related spatial approach to evaluate the determinants of poverty in Egypt, Higazi et al. (2013), identified the poor in the population by relying on individuals who earned less than one 1 Dollar as an indicator to identify the poor in the 93 Middle Delta Counties using 2006 census data. The independent variables used for the study were illiteracy ratio, dependency ration, temporary workers, educational drop out and unemployment. Each variable was tested for its spatial dependency using GeoDa. The selection of the model was based on the three information criteria: Log likelihood (L), Akaike Information Criterion (AIC), Schwarz Criterion (SC). The SEM was selected based on its highest L even though OLS and SLM had better AIC and SC than SEM as shown below:

$[(model : L : AIC : SC)(OLS : 136.125 : -260.254 : -245.058)(SEM : 149.33 : -286.661 : -271.465)(SLM : 144.38 : -274.77 : -257.05)]$ From the GeoDa output on Dependency ratio and Unemployment were significant determinants of poverty in 2006.

2.5 Spatial Analysis of Other Correlated Factors of Poverty

Some researchers sort to spatially investigate other socio-cultural, demographic and other factors that are strongly correlated with poverty.

Using spatial analysis techniques to explore the spread of the HIV infections in SSA, Kalipeni and Zulu (2010) found clusters of the disease in the region, and further analysis indicated that women were predominant among the HIV infections in the region. Poverty was found to be the main cause of the high prevalence rate of HIV cases in the region. The infections were found to be highest among females with low economic status, especially single mothers.

Achia (2014) also sorted to spatially explore the practice of female gentile mutilation (FGM) in Kenya using 2008 Kenya's Demographic and Health Survey (KDHS). The total of 8,444 women aged between 15 - 49 years were selected with a response rate of 96%. The results from the study revealed the existence of significant clusters of FGM in the North - Eastern [$RR = 12.8; p < 0.001$] and South - Western Kenya [$RR = 2.56 < 0.001$].

Also, prevalence of the mutilation was found to be 28.2% and an estimated 10.3% of the respondents (women) were in support of FGM. For the model selection, Deviance Information Criterion (DIC) was used and the best model was found to be SEM. The predictors that were found to be significantly associated with the mutilation were: religion, age, exposure to media, region, location, education, marital status and socioeconomic status.

In Ghana, a study was conducted in 2008 by Osei and Duku to explored the spatial pattern of Cholera cases in Ashanti region of Ghana using a global Moranaˆs I and Bayesian Smoothing (EBS) techniques to detect the spatial dependency of the disease and also employed the extended Mantel-Haenszel Chi-Square to analysed the trend between some demographic factors and Cholera infections in the region. The results showed a positively Moran's I of 0.271 [p-value-0.0009] indicating the clustering of high incidence rate of the disease in the region between 1997 and 2001. Also, EBS analysis revealed a high rate of clustering in Kumasi and her neighborhoods. Further, though M-H Chi-Square trend analysis, a direct relationship were established between the disease (Cholera) and Urbanization [Chi -sq = 0.000001; p - value=0.000001], Overcrowding [Chi -sq=1757.2; p -value= 0.000001] but with an inverse relationship between the disease and order (array) of neighborhood [Chi - sq= 831.38; p - value=0.00001].

Kumi and Amu (2013) also applied spatial mappings to explore the effects of spatial location and household's wealth on health insurance subscription among women in Ghana using 2008 GDHS. By the status of their wealth, the likelihood of a woman subscribing to the National Health Insurance Scheme was significantly higher among the women respondents from the middle to the richest households compares to the poorest and the poor respondents and the differences appeared to widened further in the Northern part of the country.

2.6 Evaluative Strategies to Tackle Poverty Using Non-Spatial Techniques

Other researchers used other statistical models to evaluate the possible causes of poverty and ignored any possible spatial dependency in the data. For example, Sekhampu (2013) used logistic regression as a primary tool to determine the causes of poverty in South Africa Township of Bophelong based on socioeconomic status as a dependent variable (poor and non -poor), that is whether a household is classified as poor or non-poor. A random sample of 300 households was administered with successful completion of 283 questionnaires. The findings showed that the variables that significantly explain the likelihood of a house being poor or otherwise were household size, employment and age of the household head. Whiles the age and employment status of the household head decreases the likelihood of a household being poor, the size of a household was rather having a negative effect of increasing the probability of a household being poor.

Similarly, Achia et al. (2010) also conducted multivariate analysis, employing logistic regression, to identify the major causes of household poverty in Kenya using the country’s 2003 Demographic and Health Survey. Firstly, an asset base index (poverty index) was created for each household using Principal Component Analysis (PCA) techniques. With regard to ownership of household assets, the data were recoded in to dichotomous variables [Have (1) or Don’t have (0)] and in addition to the other continuous variable (Number of people sleeping in a room), PCA was then used to generate the poverty index for each household. The multivariate analysis of the study revealed that the educational level of household heads decrease the likelihood of household falling into poverty. Also, the statistically significant variables that increase the likelihood of a house falling in to poverty were religion, region, ethnicity and age of the household. However, household size was found to statistically significant when it was tested in a univariate model.

Anyanwu (2010) examined the profile of gendered poverty in Nigeria focusing on the determinants of gendered poverty between 1980 and 1996. The data were obtained from national Consumer Survey dataset. Firstly, Foster et al. poverty index was used to generate an index for each household, and secondly, logistic regression was then applied to determine the causes of gendered poverty. The results clearly showed that female - headed households were generally poorer than their male counter parts over the years except 1992. Secondly, for education (primary, secondary and higher), poverty generally decreases as educational level increases, poverty decreases for both females and male headed households. For occupation, the rural women were predominant in agriculture and urban women were predominant in sales activities. But few women were employed in clerical and professional-technical activities. The incidence of poverty increases in sale and agricultural activities from 1980 [sale (12.2%); agric (29.0%)] to 1996 [sale (60.4%); agric (61.1%)] but professional - technical incidence of women poverty has fallen from 52.1% in 1986 to 47.4% in 1996. The "no working "female households decreases the probability of falling in to poverty across the years. Further, household sizes increases incidence of poverty for both sexes. Finally, with locations, poverty incidence increases in rural areas over the years.

As stated earlier, the complex nature of poverty has made researchers to be constantly adjusting and developing more robust tools to determine its causes, this is so because any potential strategy designed to tackle poverty need to first of all identify the factors that influence it. Some researchers used one model for monetary indicators and another model for non - monetary.

In Rwanda, Habyarimana et al. (2015) jointly used principal component analysis techniques to generate socioeconomic asset based index and regression model to determine the causes of poverty in Rwanda using 2010 Rwanda Demographic Health Survey data. According to them the Index is internally coherent and robust enough to be able to consistently produce a clear separation across poorest to the richest households for each asset included in the index. The study identified the following factors as the causes of poverty: education of household head, gender of household head, age of the household head, location (rural or urban), Region (province), and the household size. Education reduces the likelihood of been poor and house size increases the probability of been poor. Rural household were poorer than urban households; young household heads were also likely to be poorer than old household heads.

Sapaho (2014) used two econometric models, log linear with the logarithm of per capita monthly expenditure as the response variable, and logistic model with poverty status as the response variable. The research was intended to evaluate the causes of poverty in Albania using Albania Living Standard Measurement Surveys (LSMSs). Nationally random sample of 215 households were selected in 2013 for LSMS. The explanatory variables were demographic and socioeconomic indicators. The results from the two econometric models revealed that the size of the household, location of the household (rural-urban), and employment status of the household heads were statistically significant determinants of the household poverty. However, other variables such as education level of the household heads, gender, and age of the heads were not statistical significant determinants of household poverty. Accordingly, employed heads, rural households and large household size were more likely to fall into poverty than the others.

In Ghana, study was conducted in the forest and savannah zones to determine the incidence and pattern of poverty in these ecological zones using Foster, Greer, and Thorbecke indices (FGT) and Sen's poverty index. The data for the study were round three and four of Ghana Living Standard Survey (GLSS) with nationally representative samples as 4552 and 5998 households respectively. The results from the study showed that savannah areas were relatively poorer than other areas under study. Also, education, location (rural - urban), and agriculture were significantly associated with poverty in the years under study. The rural areas were generally poorer than urban areas, and households with agriculture as their main source of livelihood were poorer than households whose main occupations were non - agriculture. However, the study failed to established statistical significant differences between the standards of living of female - headed households and male - headed households (Agyeman et al., 2011).

Like the preceding studies, Ennin et al. (2011), also used logit approach to determine the causes of poverty in Ghana using round three, four and five of GSLL and nationally representative sample of round five as 8687. The households in the rounds were all classified into two distinct groups (poor and non-poor) based on the total consumption expenditure. The analysis of the results revealed that household size, location (rural-urban), region, illiteracy, agriculture and inability to attend hospital when sick were statistically significant. Household size, illiteracy, rural households, savannah zone households and inability to attend hospital when sick increase the likelihood of a households falling in to poverty and household located in urban and other areas reduces the probability of falling into poverty.

Chapter 3

Methodology

3.1 Introduction

This chapter focuses on the theoretical and conceptual frame work of Spatial Data Analysis Techniques which are the basic tools used in this research work. This is because the new technological advancement has made it possible for some researchers to use the already-programmed software without necessarily understanding the mathematical concept behind them.

The chapter is therefore designed to highlight some of the concepts and theories behind the tools used in the study

3.2 Measures of Spatial Autocorrelation

Spatial Autocorrelation is an assessment or the measure of correlation of a variable with itself over space. Spatial autocorrelation basically involves comparison of two types of information: similarity among attributes and similarity of location. The ways in which the former can be measured depends on the type of data used, while the calculation of spatial proximity depends on the type of object (Goodchild, 1986). The two methods commonly used to measure Spatial Autocorrelation are;

- Moran's I
- Geary's C

This study employed Moran's I to measure Spatial Autocorrelation. According to Getis-Ord (1992), Moran's I is more preferable because it is less affected by deviations from the Normal or Gaussian distribution than Geary's C and that

Moran's I is consistently more powerful than Geary's C. Also, Goodchild (1986) noted that the obvious advantage of one over the other is that the Moran index is arranged so that its extremes match the intuitive notions of positive and negative values of the already known Pearson correlation coefficient, whereas the Geary index uses a more confusing scale.

3.3 Theoretical Background of Moran's I

Moran's autocorrelation index (often denoted as I) is an extension of Pearson Product Moment Correlation Coefficient to a univariate series (Paradis, 2013). Recall that Pearson Correlation Coefficient (denoted as ρ) between two variables both with sample size n is given by:

$$\rho = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{[\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2]^{\frac{1}{2}}} \tag{3.1}$$

Where $\bar{x}$ and $\bar{y}$ are the sample means of both variables. The ρ measures whether, on average, x_i and y_i are associated. For a single variable, say X, I will measure whether x_i and x_j with $i \neq j$, are associated. Note that with ρ , x_i and x_j are not associated since the pairs (x_i, y_i) are assumed to be independent of each other.

In the study of spatial patterns and processes, we may logically expect that close observations are likely to be similar than those far apart. To quantifies this, to each pair (x_i, y_i) is associated with a WEIGHT (w_{ij}). These weights are sometimes referred to as neighboring functions (Paradis 2013). I is given as;

$$I = \frac{n}{S_0} \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{3.2}$$

where $S_0 = \sum_i \sum_j w_{ij}$ i.e S_0 is the sum of w_{ij} $w(ij)$ is the weight between observation i

and j n is the number of observations (points or clusters) x_i is the variable value at a particular location $x(j)$is the variable value at another location

Note that the numerator of I in (3.2); $\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})$ is a gamma statistic with x_i and x_j as random variables and as such, it is scale dependent. In order to make it scale independent, we divide it by S_0 and by a consistent estimator $\frac{\sum_{i=1}^{n}(x_i-\bar{x})^2}{n}$.

The attribute similarity measure used by the Moran's I, makes it analogous to a covariance between the value of a pair of objects c_{ij};

$$c_{ij} = (x_i - \bar{x})(x_j - \bar{x}) \tag{3.3}$$

Where $\bar{x}$ is the mean of the attribute variable.

Instead of the two variables x and y, c_{ij} measures the covariance between the value of the variable at one place and its value at another place. The weight matrix w_{ij} can be defined either by contiguity (whether clusters share common boundaries or vertices) or distance (whether clusters geometric centroids are within certain distance thresholds). For contiguity, the measure is based on the information with regards to the size and shape of the observational units represented on a map. From this, we can establish which neighborhood units have borders that touch. For the distance, the location of Cartesian space represented by latitude and longitude is one source of information. This information would allow us to calculate distances from any point in space. Observations that are near should reflect a greater degree of spatial dependence than those more distant from each other. (LeSage, 1999).

In this study, the elements of the weight matrix are specified as inverse-distance matrix according to the spatial distance between the observations. The spatial matrix indicates the spatial relationship among all the observations, and the value of the elements in the matrix is equal to:

$$w_{ij} = \frac{1}{distancebetweeniandj}$$

The distance between observations i and j is obtained by computing:

$$Distancebetween Iandj = [(Lat_i - Lat_j)^2 + (Lont_i - Lont_j)^2]^{\frac{1}{2}} \tag{3.4}$$

Where Lat_i and Lat_j represent the latitude and longitude of the observations respectively. So according to the way that the matrix is constructed, the higher value of element w_{ij} indicates the shorter distance between i and j, and vice versa (Jian 2010).

3.3.1 Standardizing Weight Matrix

The weight matrix is often row standardized as;

$$w_{ij}^s = \frac{w_{ij}}{\sum_i \sum_j w_{ij}} \tag{3.5}$$

Such that $\sum_i \sum_j w_{ijs} = 1$

The row standardization has two implications; equal weight across neighbours of the same cluster and the sum overall elements of the row standardized weight matrix is equal to the total number of observations (n). That is in (3.2), $\sum_i \sum_j w_{ij} = n$

Therefore equation (3.1) becomes

$$I^s = \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{3.6}$$

Moran's I of standardized spatial weight matrix W in matrix notation is given as:

$$I^s = \frac{(X - \bar{X})^T W (X - \bar{x})}{X - \bar{X})^T (X - \bar{x})} \tag{3.7}$$

3.3.2 Interpretation of Moran's I

- If clusters with above-average (below) attribute are neighbours of clusters with above-average (below) attributes, then the cross-average product term $(x_i - \bar{x})(x_j - \bar{x})$ becomes positive, making $I^s > 0$ and implies that there is positive spatial auto-correlation (SAC), (Torres et al 2011). In other words, features with similar locations also tend to be similar in attribute.

- On the other hand, if clusters with above-average (below) attributes are surrounded by neighbouring clusters with below - average (above) attributes, makinga˜$I^s < 0$ then it implies that there is negative SAC.

- The closer I^s gets to zero, the weaker the evidence to support SAC. This implies that attributes are independent of each other.

3.4 Local Indicator of Spatial Autocorrelation (LISA)

A major limitation of Moran's I is that, it cannot provide information on the specific locations of spatial patterns rather, it only indicates the presence of spatial autocorrelation globally. To localize the presence and magnitude of SAC, a measure such as Anselin's local indicator of spatial autocorrelation (LISA) is necessary. LISAs are simple local disaggregation of global measures of spatial autocorrelations (Holt 2007).

The local version of Moran's I define on ith location is (Kriaa et al 2011):

$$\frac{(x_i - \bar{x})}{m_0} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x}) \qquad (3.8)$$

Where $m_0 = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n}$ $x_i$is the observation at each ith location x_j is an observation at all other locations

Basically, LISA can be used to access the significance of spatial concentrations or clusters, as a diagnostic tool for local instability (non-stationary), significant outliers, and spatial regimes (Anselin, 1995).

3.5 Moran's Scatter Plot

Moran's I statistic gives a formal indication of the degree of linear associations between a vector observed value, x and a weighted average of the neighbouring values, or spatial lag (Anselin, 1996). Considering the row standardized form of Moran's I:

$$I^s = \frac{(X-\bar{X})^T W(X-\bar{x})}{X-\bar{X})^T (X-\bar{x})}$$

Anselin (1996) stated that since the Xs are in deviations from their mean, I is formally equivalent to a regression coefficient in a regression of W_x on X. For example, to determine the Moran's I of Crime rate in Ghana, then we will have W-Crime (Wx) against Crime (X) as shown below The interpretation of Moran's

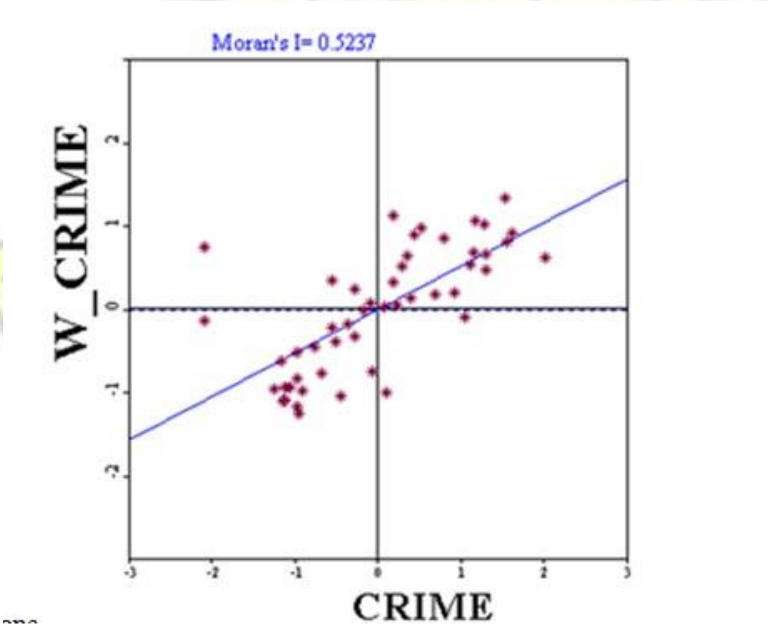

Figure 3.1: Moran Scatter Plot

I as a regression coefficient provides a way to visualize linear association between X and W_x in the form of a bivariate scatter plot of W_x against X. This plot is called Moran's scatter plot which has Moran's I as a slope (Anselin, 1996).

3.5.1 Interpretation of Moran's scatter plot.

The four different quadrant of the scatter plot identify four types of spatial associations, a cluster and its neighbours (Samet et al, 2010);

- (HH) a high attribute cluster with high attribute neighbours (quadrant I);
- (LH) a low attribute cluster surrounded by high attribute neighbours (quadrant II);
- (LL) a low attribute cluster surrounded by a low attribute neighbours (quadrant III) and
- (HL) a high attribute cluster surrounded by low attribute neighbours

Quadrant I and III pertain to positive forms of spatial dependence. They exhibit what Anselin (2005) called spatial clusters while the remaining two quadrants represent negative spatial dependence are also known as spatial outliers.

3.6 Outliers and leverages

Points in the scatter plot that are extreme with respect to the central tendency reflected by the regression slope may be outliers in the sense that they do not follow same process of spatial dependence as the bulk of the other observations. They could thus be considered as local non - stationary. The presence of outliers may also point to problems with specification of spatial weight matrix or with a spatial scale which the observations are recorded (Anselin, 1996).

Similarly, observations that exert a large influence or leverage on the regression slope are of interest, again, particularly if they are spatially clustered or correspond to boundary points. Importance of Moran scatter plot.

I Quantifying spatial association in to four quadrants based on the similaritiesor dissimilarities with the neighbours.

II Identifying observations that are outliers relative to the global measures ofspatial autocorrelation given by Moran's

III Discovering different spatial regimes in the degree (slope) of spatial association.

IV Finding observations that exert a large influence (leverage) on the Moran's coefficient

V Identifying the leverage and influence of observation that suffer from bound-ary effects

VI Suggesting problems with specification of the spatial weight

3.7 Residual Maps

According to Anselin (2005), the most useful residual map in ESDA is probably a standard deviation map, since it clearly illustrates patterns of over or under prediction, as well as the magnitude of the residuals, especially those greater than two standard deviational units. The "visual inspection "of residual maps will suggest the presence or otherwise of spatial autocorrelation, but this requires a formal test before it can be stated more exclusively. Residuals should be randomly distributed. Clusters of similar colours could indicate spatial autocorrelation.

The presence of the outliers suggests that the independent variables alone in the model may not be sufficient to explain the variations in the dependent variable.

Selecting these locations and linking with other graphs or maps might shed light on which variables should be included in an improved regression specification (Anselin, 2005).

3.8 Plotting Residuals

Plotting the residual against unique ID variables such as *Poly* – *ID* also helps in identifying unusually significantly large residuals which may be removed to improve the prediction power of the model. It also helps in accessing under prediction and over prediction.

Positive residuals (this indicates under-prediction areas), mean the rate of occurrences of the phenomenon/attribute under study, say poverty, are much higher in these areas than the model predicts. Also, negative residuals (indicating over prediction areas), mean the rate of occurrences of the phenomenon under study, say poverty, are much lower in these areas than the model predicts.

3.9 Plotting Residuals vs. Predicted Values

It helps in testing for the constant variances of the residuals, heteroskedasticity, and also finds outliers. The residuals should be scattered randomly and should not make any funnel like shape. A straight line of residuals runs diagonally across the bottom of the plot and represents clusters with zero rate of the occurrence of the phenomenon under study.

3.10 Modelling Spatial Regression

Spatial Regression models are used as a Confirmatory Spatial Data Analysis after ESDA. Two of the common spatial regression models (Anselin, 1999) are; Spatial

Lag Model (SLM) and Spatial Error Model (SEM). Ordinary Least Square (OLS) model is often used as a null model for comparative analysis.

3.10.1 The Ordinary Least Square Model

The Ordinary Least Square regression takes the form;

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki} + \epsilon_i \qquad (3.9)$$

Where i =

1...n

y_i is normally distributed n is the

number of units studied

$_i$ are i.i.d.N $(0,\sigma^2)$

In matrix form, (3.10) can be written as

$$y = X\beta + \epsilon \qquad (3.10)$$

The method of Ordinary least squares (OLS) estimation is referred to as a Best Linear Unbiased Estimation (BLUE). The OLS estimate β by minimizing the sum of squared prediction errors, hence, least squares. In order to obtain BLUE property and make statistical inferences about the population regression co efficient from the estimated b, certain assumptions about the random errors of the regression equation need to be made. A few pertaining to the purpose of this study are:

1. the mean of the residuals is zero (no misspecifications)
2. the residuals are uncorrelated and hence a constant variance (homoskedastic):
3. the distribution of the residuals follows a normal distribution

When conducting regression analysis with data aggregated to geographic areas such as districts or cluster (an irregular), it is common to find spatially auto correlated residuals. Residuals are usually spatially positively auto - correlated such that high residuals tend to cluster in space and low - valued residuals also tend to show geographic clustering (Higazi et al, 2013).

When spatial auto - correlation exist, in (3.11) above, the error term has to take this auto - correlation into account as follows;

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki} + U_i \tag{3.11}$$

Where U_i is spatially auto - correlated error term, it is distributed as multivariate term; $U_i = [u_1,...u_n)]^T$

$u \approx MV\,N(0,v)$

The spatial effects falls within the matrix U, arising from the contiguity structure weight matrix (Higazi et al, 2013) as follows;

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki} + \rho \sum_{j \in N_i} w_{ij} y_j + \epsilon_i \tag{3.12}$$

Where ρ is a spatial effect parameter, w_{ij}

is the normalized weight matrix

N_i are the number of contiguous units for unit i and

$\rho \sum_{j \in N_i} w_{ij} y_j$ expresses how the regression equation is affected by the spatial effect.

Equation (3.7) is generally referred to as spatial auto-regression. It has incorporated spatial dependence in two distinct ways (Anselin 1999);

(a) as an additional repressor in the form of a spatially lagged dependent variable Wy or

(b) in the error structure $[E(e_i,e_j)] \neq 0$

The 1st case (a) is referred to as special lag model and the second case (b) as special error model.

3.11 The Spatial Lag Model

Spatial Lag Model is appropriate when the focus of interest is the assessment of the existence and strength of spatial interaction (Anselin, 1999). Also, according to Ward and Gleditech (2007) SLM is appropriate when we believe that the value of y in one unit i are directly influenced by the values of y found in j's "neighbours ". This influence is above and beyond other covariates specific to i. For SLM to be appropriate, the dependent variable must be considered as a continuous variable.

Formally, a spatial lag model is expressed by (Higaz et al, 2013) as

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki} + \rho \sum_{j \in N_i} w_{ij} y_j + \epsilon_i \tag{3.13}$$

where, ρ is the spatial lag coefficient

$\sum_{j\in N_i} w_{ij}y_j$ denotes the interactive effect of dependent from adjacent region i and j.

In matrix form, SLM can be written as;

$$y = X\beta + \rho W y + \epsilon \tag{3.14}$$

is a vector of error terms $y$is an $n \times 1$vector of observation on the dependent variable W is an $n \times n$ spatial weight matrix ρ is a spatial auto - regressive parameter

X is $n{\times}k$ matrix of observation on the exogenous variable, with an associated of regressive coefficient.

The matrix ρWy is used as an additive explanatory variable, calculated by using spatial lagged dependent variable according to the weight matrix.

The reduced form of equation (3.11) is obtained as follows;

$$y = \rho W y + X\beta + \epsilon, y = (I - \rho W)^{-1}(X\beta + \epsilon) \qquad (3.15)$$

The term $(I-\rho W)^{-1}$ which is also known as Leontief expression can be expressed as;

$$(I - \rho W)^{-1} = 1 + \rho W + \rho^2 W^2 + \rho^3 W^3 + ... \qquad (3.16)$$

From (3.16) it is noted that, the decision $y_i$variable is linked to all the x_i in the system through a so called spatial multiplier.

Also (3.16) illustrate how the dependent variable y_i at i determined by the error term at all location in the system, and not just the error i. Further, it indicates that as the distance between observation increases, the spatial effect decreases. The error variable covariance matrix (Anselin, 1999) is of the form$E(\epsilon^T \epsilon) = \delta^2(\theta)$. Where $\theta$is a vector of parameter, such as coefficient in an error process.

The OLS Estimator of the SLM Parameter ρ

The estimation of SLM by OLS leads to biased and inconsistent parameter estimates. Consider the basic spatial lag model (excluding the exogenous variables,X_1,X_2,...,X_n) as shown below. Comparing (3.17) to OLS regression of the form$y = X\beta + \epsilon$, we have; $\hat{\rho}$ $= [(Wy)^T Wy]^{-1} - (Wy)^T y$

$$\hat{\rho} = [(Wy)^T Wy]^{-1} - (Wy)^T(\rho W y + \epsilon)$$

$$\hat{\rho} = \rho + [(Wy)^T Wy]^{-1} - (Wy)^T \epsilon \qquad (3.17)$$

Taking expectation on both sides of (3.18), we obtained

$$E(\hat{\rho}) = \rho + E([(Wy)^T Wy]^{-1} - (Wy)^T \epsilon) \qquad (3.18)$$

It is clear from (3.19) that the expectation of the last term is not equal to zero, that is

$$E((Wy)^T\epsilon) = E([W(I-\rho W)]^T\epsilon)$$
$$= E([\epsilon^T(I-\rho W)^{-1}W^T\epsilon] \neq 0$$

Since $E(\hat{\rho}) \neq \rho$, then OLS estimator $\hat{\rho}$ is a biased estimator of ρ.

For consistency, an estimator $\hat{\theta}$ for a parameter θ is said to be consistent, if it converges in probability to θ, that is:

$$\lim_{n\to\infty} P(|\hat{\theta}_n - \theta| > \delta) = 0, \delta > 0$$

In probability, the convergence could be written as probability limit (*plim* operator), hence $plim\hat{\theta}_n = \theta$

To explain the fact that the estimator depends on the sample size n, we use the subscript n.

Now taking plim of (3.18) and applying product rule, we obtain:

$$plim\hat{\theta}_n = \rho + plim[(Wy)^TWy]^T \times plim(Wy)^T\epsilon$$

or

$$plim\hat{\theta}_n = \rho + plim[(Wy)^TWy]^T \times plim\frac{1}{n}(Wy)^T\epsilon \tag{3.19}$$

but,

$(Wy)^T\epsilon = \epsilon^TW(I-\rho W)^{-1}\epsilon$ then (3.20) will translates into

$$plim\hat{\theta}_n = \rho + plim[(Wy)^TWy]^T \times plim\frac{1}{n}\epsilon^TW(I-\rho W)^{-1}\epsilon \tag{3.20}$$

Inspecting the last term of (3.21), it is clear that it consist of a quadratic form in error term, hence for values of $\rho \neq 0$, the expression with not be zero. Thus, $plim\hat{\theta}_n \neq \rho$

This indicates that OLS estimator of $\hat{\theta}$ of the SLM parameter θ is inconsistent.

3.11.1 The Spatial Error Model (SEM)

SEM is appropriate when the concern is with correcting for the potentially biasing influence of the auto-correlation, due to the use of spatial data (irrespective of whether the model is spatial or not) (Anselin, 1999).

Also, unlike SLM, if we believe that y is not influenced by the value of y as such among neighbours, but rather that there is some spatially clustered feature that influences the value of y for I and its neighbours but is omitted from the specification, then we may consider SEM with spatially correlated errors. SEM takes the form

$$y_i = \sum_j x_{ij}\beta_j + \epsilon_i \tag{3.21}$$

where, $\epsilon_i = \lambda \sum_j w_{ij}\epsilon_j + u_i$

In matrix form we have

$$y = X\beta + \epsilon \tag{3.22}$$

Where

$\epsilon = \lambda W\epsilon + u$ and $\epsilon \approx N(0, \sigma^2 I_n)$

can be expressed as

$(I - \lambda W)\epsilon = u$

$\epsilon = (I - \lambda W)^{-1}u$

The error variance-covariance matrix follows as

$E(\epsilon\epsilon^T) = E(I - \lambda W)^{-1}u((I - \lambda W)^{-1}u)^T$

$E(\epsilon\epsilon^T) = (I - \lambda W)^{-1}E(uu^T)(I - \lambda W^T)^{-1}$ Under standard assumption of i.i.d,

error, $\hat{\mathrm{I}}^1_4$ with

$E(uu^T) = \sigma^2$

this expression simplifies to,

$$E(\epsilon\epsilon^2) = \sigma^2(I - \lambda W)^T[(I - \lambda W)]^{-1} \tag{3.23}$$

3.11.2 OLS in Presence of Residual Autocorrelation

OLS estimates of SEM parameters will be unbiased, but inefficient as a result of non-diagonal structure of the error variance covariance matrix in (3.23) above.

Consider the SEM models;
$y = X\beta + \epsilon$; $\epsilon = \lambda W\epsilon + u$

An estimator $\hat{\theta}$ is be unbiased estimator of the parameter θ if

$E(\hat{\theta}) = \theta$
Now from OLS estimates, we have $\hat{\beta}$

$= (X^T X)^{-1} X^T y$

and with $y = X\beta + \epsilon$, we obtained

$$\hat{\beta} = (X^T X)^{-1} X^T (X\beta + \epsilon) = \beta + (X^T X)^{-1} X^T \epsilon \tag{3.24}$$

Taking expectation of (3.24)
$E(\hat{\beta}) = \beta + E((X^T X)^{-1} X^T \epsilon)$

$= \beta + (X^T X)^{-1} X^T E(\epsilon)$

$= \beta$

Thus, OLS estimator $\hat{\beta}$ is unbiased estimate of β.
For efficiency, we have

$Cov(\hat{\beta}) = E[(\hat{\beta} - \beta)(\hat{\beta} - \beta)^T]$
$= E((X^T X)^{-1} X^T \epsilon)((X^T X)^{-1} X^T \epsilon)^T$

$= E((X^T X)^{-1} X^T \epsilon\epsilon^T X (X^T X)^{-1})$

$= (X^T X)^{-1} X^T E(\epsilon\epsilon^T) X (X^T X)^{-1}$

From (3.23) $E(\epsilon\epsilon^2) = \sigma^2 (I - \lambda W)^T [(I - \lambda W)]^{-1}$ and by substitution, we have

Then,

$Cov(\hat{\beta}) = (X^T X)^{-1} X^T \sigma^2 (I - \lambda W)^T [(I - \lambda W)]^{-1} X (X^T X)^{-1}$
This can be written as

$Cov(\hat{\beta}) = \sigma^2 ((X^T X)^{-1} X^T \Omega X (X^T X)^{-1})$

Where $\Omega = (I - \lambda W)^T[(I - \lambda W)]^{-1}$

The error variance covariance matrix Ω is non - diagonal making OLS estimator inefficient. From the above, it is obvious that the multidimensional nature of spatial dependence will limit OLS method of producing consistent parameter estimates.

3.11.3 Estimation of Model Parameters

Several references have written about parameter estimation of spatial autoregressive model. Some of these include Maximum Likelihood Estimation (MLE) (Lesage and Pace 2009; Anselin, 2003), Bayesian estimation, Generalized Method of Moments (GMM) estimation (Zhang and Zhu (2012)).

Lesage and Pace (2009) noted that estimation of spatial models by least squares can lead to inconsistent estimates of the regression parameters and inconsistent estimation of standard errors for models with spatially lagged dependent variables.

In contrast, maximum likelihood is consistent for these models. Lu and Zhang (2010) stated that GMM was close to MLE in terms of model fitting and noted however that, MLE is much easier in computation and robust to non-normality and outliers. Lu and Zhang (2010) also showed that the Bayesian method with heteroskedasticity did not effectively estimate the spatial autoregressive parameters as MLE does but produced very small biases for the regression coefficients of the model when few outliers exist.

3.11.4 The MLE Parameters Estimates of SLM

The errors of SLM are identically and normally distributed with the expected value and variance given as:

$E(\epsilon) = 0$ and $Cov(\epsilon) = \sigma^2 I$

Thus, $\epsilon \sim N(0, \sigma^2 I)$

Thus, the pdf of the disturbance variable of cluster I is given as;

$$f(\epsilon_i, 0, \sigma^2 I) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{(-\frac{1}{2\sigma^2}(\epsilon_i - 0)^2)} \tag{3.25}$$

Hence the joint density function for n clusters, $f_{\epsilon_1}, \ldots, f_{\epsilon_n}$ is given as $f_{\epsilon_1}, \ldots, f_{\epsilon_n}(\epsilon_i, 0, \sigma^2 I) = \Pi_i^n f(\epsilon_i, 0, \sigma^2)$

Using (3.17)we obtain,

$$f(\epsilon_i, 0, \sigma^2 I) = \frac{1}{(2\pi)^{\frac{n}{2}} (\sigma^2)^{\frac{n}{2}}} e^{(-\frac{1}{2\sigma^2} \sum_i^n \epsilon_i^2)}$$

Now by letting $\sum \epsilon_i^2 = \epsilon^T \epsilon$, we have

$$f(\epsilon_i, 0, \sigma^2 I) = \frac{1}{(2\pi)^{\frac{n}{2}} (\sigma^2)^{\frac{n}{2}}} e^{(-\frac{1}{2\sigma^2} \epsilon^T \epsilon)} \tag{3.26}$$

The joint density function for y, $f_{y_1}, \ldots, f_{y_n}$, by transformation is given by

$$f(y) = f(\epsilon) |\frac{\partial \epsilon}{\partial y}| \tag{3.27}$$

From the Equation of SLM : $y = \rho W y + X\beta + \epsilon$, developing error equation, we have,
$\epsilon = y - \rho W y - X\beta$

$$\epsilon = (I - \rho W) y - X\beta \tag{3.28}$$

Then the likelihood function is given as $L(\sigma^2, \epsilon | y) = (\frac{1}{2\pi\sigma^2})^{\frac{n}{2}} e^{(-\frac{1}{2\sigma^2} \epsilon^T \epsilon)}$

$$L(\sigma^2, \epsilon | y) = (\frac{1}{2\pi\sigma^2})^{\frac{n}{2}} (J) e^{(-\frac{1}{2\sigma^2} \epsilon^T \epsilon)} \tag{3.29}$$

The Jacobian function from the (3.17) can be performed by differentiating its equation with respect to the dependent variable y:

Then from $\epsilon = y - \rho W y - X\beta$, we have

$$J = |\frac{\partial \epsilon}{\partial y}| = |I - \rho W| \tag{3.30}$$

Substituting (3.29) and (3.31) into (3.30), the following equation is obtained:

$$L(\sigma^2, \beta\sigma^2|y, x) = (\frac{1}{2\pi\sigma^2})^{\frac{n}{2}}|I - \rho W|e^{(-\frac{1}{2\sigma^2}[(I-\rho W)y-X\beta]^T[(I-\rho W)y-X\beta])} \quad (3.31)$$

Then taking natural logarithm of (3.32), the following equation is obtained:

$$InL = \frac{n}{2}In(\frac{1}{2\pi\sigma^2}) + In|I - \rho W| - \frac{1}{2\sigma^2}[(I - \rho W)y - X\beta]^T[(I - \rho W)y - X\beta] \quad (3.32)$$

Letting $G = I - \rho W$ then we have

$$InL = \frac{n}{2}In(\frac{1}{2\pi\sigma^2}) + In|I - \rho W| - \frac{1}{2\sigma^2}[Gy - X\beta]^T[Gy - X\beta] \quad (3.33)$$

Parameter estimate can be performed by maximizing natural logarithm of Equation (3.30) with respect to β.

$$\frac{\partial(InL)}{\partial\beta} = 0$$

this implies;

$$\frac{\partial InL}{\partial\beta} = \frac{(0 - X^TGy - X^TGy + X^TX\beta + (\beta^TX^TX)^T)}{2\sigma^2}$$

$$\hat{\beta} = (X^TX)^{-1}X^TGy \quad (3.34)$$

Substituting $G = I - \rho W$ into (3.25) we have;

$$\hat{\beta} = (X^TX)^{-1}X^T(I - \rho W)y \quad (3.35)$$

The maximum likelihood estimator for β depend on the unknown parameter ρ.

Decomposing (3.26) we obtained the following $\hat{\beta} = \beta_0 + \rho\beta_L$

Where $\beta_0 = (X^TX)^{-1}X^TY$ and $\beta_L = (X^TX)^{-1}X^TWY$

Inspection shows that β_0 is the coefficient vector from the OLS regression of y on X; while β_L is from the OLS regression of Wy on X. So if $(\hat{\rho})$ is known, we could compute the ML estimate of β.

The maximum likelihood residuals also depend on ρ and can also be decomposed as follows:

$e_{ML} = y - \rho Wy - X\hat{\beta}$ but $\hat{\beta} = \beta_0 + \rho\beta_L$ thus $e_{ML} =$

$y - \rho Wy - X(\beta_0 + \rho\beta_L) = y - \rho Wy - X\beta_0 + \rho X\beta_L$

$= y - X\beta_0 - \rho(Wy - X\beta_L)$

$$e_{ML} = e_0 - \rho e_L \tag{3.36}$$

Next, the residuals of these two OLS regressions is written as

$e_0 = y - X\beta_0$ $e_L =$

$Wy - X\beta_L$

Estimating σ^2

Such as the parameter estimate β, estimate σ^2can be performed by differentiating Equation (3.21) with respect to σ^2, This implies;

$$\frac{\partial In(L)}{\partial\sigma^2} = 0$$

$$\frac{\partial In(L)}{\partial\sigma^2} = -\frac{n}{(2\sigma^2)} + \frac{1}{2(\sigma^2)^2}([Gy - X\beta]^T[[Gy - X\beta]])$$

$$= 0 - n + \frac{1}{\sigma^2}([Gy - X\beta]^T[[Gy - X\beta]])$$

$$\sigma^2 = \frac{1}{n}([Gy - X\beta]^T[[Gy - X\beta$$

$\rho W)y - X\beta]^T[[(I - \rho W)y - X\beta]])$]]) So that, the estimate of $\hat{\sigma^2} = \frac{1}{n}([(I -$

$\hat{\sigma}^2$ can be expressed in terms of e_0 and e_L, using (3.28), as:

$$\hat{\sigma^2} = \frac{e_{ML}^T e_{ML}}{n}$$

$$\hat{\sigma^2} = \frac{(e_0 - \rho e_L)^T(e_0 - \rho e_L)}{n} \tag{3.37}$$

So once again σ^2 could be estimated if $\hat{\rho}$ were known.

Estimating ρ

Now substituting the estimates of β and σ^2 into (3.23) and simplify we obtained the concentrated likelihood function that is nonlinear in ρ as shown below:

$$In(L^*) = -\frac{n}{2}In(\pi) - \frac{n}{2}In(y - \rho Wy) - (y - \rho Wy) + In|I - \rho W|$$

This can also be expressed in terms of e_0 and e_L as:

$$In(L^*) = C + \frac{n}{2}In[\frac{(e_0 - \rho e_L)^T(e_0 - \rho e_L)}{n}] + In|I - \rho W|$$

Where C does not involves any unknown parameters. We can now maximize $In(L^*)$ with respect to ρ and obtain the ML estimate of this parameter, and work backwards.

In detail, the estimation steps are:

1. Regress y on X: this gives β_0 Compute the residual $e_0 = y - X\beta_0$

2. Regress Wy on X: this gives β_0 Compute the residual $e_L = Wy - X\beta_L$

3. Find the ρ that maximizes the concentrated log-likelihood function. Call it $(\hat{\rho})$

4. Given $(\hat{\rho})$, compute $\hat{\beta} = \beta_0 + \rho\beta_L$ and $\hat{\sigma}^2 = (\underline{\qquad\qquad} e^0 - \rho \hat{e}^L)^T(e^0 - \rho \hat{e}^L)$. ρ takes n feasible values in $\frac{1}{\lambda max} < \rho < \frac{1}{\lambda min}$

3.11.5 MLE Parameters Estimation of the SEM

Estimation of SEM of MLE follows multivariate normal distribution. From the SEM Equations;

$$y = X\beta + \epsilon \tag{3.38}$$

$$\epsilon = \lambda W\epsilon + u \tag{3.39}$$

And $u \sim (0, \sigma^2 I)$

Equation (3.39) and (3.40) can be expressed as:

$y - X\beta = \epsilon$

$(I - \lambda W)\epsilon = u$ (since is not iid, unlike in SLM, we have to use u in the Log likelihood)

$A\epsilon = u$, where $A = (I - \lambda W)$

Hence we have $u = A(y - X\beta)$

Differentiating u w.r.t y to obtained the Jacobian, J, we have

$$J = |\frac{\partial u}{\partial y}| = |I - \lambda W|$$

Then from (3.27) we have

$$f(u_i, 0, \sigma^2 I) = \frac{1}{(2\pi)^{\frac{n}{2}}(\sigma^2)^{\frac{n}{2}}} e^{-(\frac{1}{2\sigma^2}uu^T)}$$

$$f(y) = f(u)|\frac{\partial u}{\partial y}|$$

The likelihood for y of the SEM is obtained as: $L(\sigma^2, \beta, \rho|x, y) = (\frac{1}{2\pi\sigma^2})^{\frac{n}{2}}(J)e^{(-\frac{1}{2\sigma^2}uu^T)}$

$$= (\frac{1}{2\pi\sigma^2})^{\frac{n}{2}}|I - \lambda W|e^{(-\frac{1}{2\sigma^2}[A(y-X\beta)]^T[A(y-X\beta)])}$$

the log - likelihood can be expressed as:

$$In(L) = -\frac{n}{2}In(2\pi) - \frac{n}{2}In(2\pi) + In|A| - \frac{1}{2\sigma^2}[(y - X\beta)]^T A^T A[(y - X\beta)] \quad (3.40)$$

$$= -\frac{n}{2}In(2\pi) - \frac{n}{2}In(2\pi) + In|A| - \frac{1}{2\sigma^2}[y^T A^T Ay - 2y^T A^T AX\beta + \beta^T X^T AX\beta]$$

$0 = -2y^T A^T AX + 2X^T A^T AX\beta$

hence,

$$\hat{\beta} = (X^T A^T X)^{-1} X^T A^{-1} AX \quad (3.41)$$

$$\frac{\partial In(L)}{\beta} = \frac{\partial(-\frac{n}{2}In(2\pi) - \frac{n}{2}In(2\pi) + In|A| - \frac{1}{2\sigma^2}[y^T A^T Ay - 2y^T A^T AX\beta + \beta^T X^T A}{\partial\beta}$$

Now, β could be estimated using Generalized Least Square (GLS) and an estimate of $\sigma^2$is similar to the SLM case.

The concentrated log - likelihood is:

$$In(L^*) = C + \frac{n}{2}In[\frac{e^T A^T Ae}{n}] + In|A|$$
Where $\epsilon = y - X\beta_{GLS}$ and C is a constant

Since β_{GLS} itself depend on ρ, (unlike SLM case), Anselin suggested an iterative procedure, essentially as follows (Vito, 2010):

1. Regress y on X: Call the coefficient estimate β_{OLS} and compute the residual vector $\epsilon = y - X\beta_{OLS}$

2. Use this *e* in the concentrated log - likelihood, and optimize to find (ρ).

3. Use $\hat{\lambda}$ to compute the GLS estimator β_{GLS} and then a new residual vector $\epsilon = y - X\beta_{GLS}$

4. First time or if the residuals have not converged: go back to step 2 and re-estimate λ. Otherwise: go to step 5.

5. At this point we have a converged estimate of λ, (say $\hat{\lambda}$) and the associated residual vector e, and a GLS estimator of β. We can now estimate σ^2 by $\frac{(e^T A^T Ae)}{n}$

3.12 Tests on Spatial Dependence in the Errors

We present six tests on spatial dependence in the errors terms of a standard regression model. If the disturbance are spatially correlated, the assumption of a spherical error covariance matrix,
$Cov(\epsilon) = E(\epsilon\epsilon^T) = \sigma^2 I$ is violated.
In the following, we present six tests for determining spatial dependence in the error term. The Moran test, A Lagrange Multiplier test for Spatial Error Dependence [LM(err)], A Lagrange Multiplier test for lag dependence [LM(lag)), Robust Lagrange Multiplier Tests for Errors, Robust Lagrange Multiplier Tests for

Lag and Lagrange Multiplier SARMA test. While the Moran test for spatial error autocorrelation is general test, the LM are more specific. They provide a basis for choosing an appropriate spatial regressive model.

Significance of LM(err) points to a spatial error as alternative to OLS model while significance of LM(lag) points to a spatial lag model as alternative to OLS (Anselin,1988).

3.12.1 The Moran Test

The Moran's I statistic for regression residuals using an unstandardized weight matrix W^* is given as,

$$I = \frac{n}{S_0}\frac{e^T W^* e}{e^T e} \quad (3.42)$$

With $\sum_i \sum_j W^*_{ij} = S_0$ Where e is $n \times 1$ a vector of OLS residuals

With a standardized weight matrix W, the Moran's I for e is used simplified to:

$$I = \frac{e^T W e}{e^T e} \quad (3.43)$$

because of $S_0 = n$

I is interpretable as the coefficient of the as OLS regression of W_e of e.

Significance test of Moran's I

The standardised Moran's I coefficient follows a standard normal distribution under the following null hypothesis of no spatial dependence:

Null hypothesis H_0 : Absence of spatial dependence,

Alternative hypothesis H_a: Presence of spatial dependence,

The cause of spatial dependence under H_a is unspecified, that is the underlying spatial process is not specified. Thus the Moran test is a general test for detecting spatial auto correlation (Anselin, 1988).

Test statistic:

$$Z(I) = \frac{(I - E(I))}{\sqrt{Var(I)}} \tag{3.44}$$

Expected value:

$$E(I) = \frac{Tr(MW)}{n - k} \tag{3.45}$$

Projection Matrix:

$$M = I - X(X^T X)^{-1} X^T \tag{3.46}$$

Where $X(X^T X)^{-1} X^T$ is the hat matrix (H) **Variance:**

$$Var(I) = \frac{(tr(MWMW)^T) + tr(MWMW) + [tr(MW)]^2}{(n-k)(n-k+2)} - [E(I)]^2 \tag{3.47}$$

3.12.2 Lagrange Multiplier Test for Spatial Error Dependence

Unlike the Moran tests which rely on well - structured hypothesis, the Lagrange multiplier test for spatial dependence (LM err) is based on the estimation of the auto correlated errors; $\epsilon = \lambda W \epsilon + u$under the null hypothesis

$H_0 : \lambda = 0$

This means that OLS estimation of the model$y = X\epsilon + \epsilon$suffices for conducting the LM error test. The alternative hypothesis H1 claims the spatial auto regression coefficient is unequal to zero.

$H_1 : \lambda$ 6= 0

Test statistic:

$$LM_{err} = [\frac{\frac{e^T W e}{S_2}}{T}] \tag{3.48}$$

with $S^2 = \frac{(e^T W e)}{n}$ and $T = tr[(W + W^T)W]$

The test statistic is distributed as chi-square with one degree of freedom. Critical value (significance level α): chi-squared $(1;1 - \alpha)$ **Test decision:**

$LM_{err} > chisquared(1;1 - \alpha)$

Reject H_0

LM_{err} pertain to Spatial Lag model as alternative to OLS if it is statistically significant at a given level of significance (α).

3.12.3 Lagrange Multiplier Test for Spatial lag Dependence

Spatial dependence in regression model may not only be reflected in the errors. Instead it may be accounted by entering a spatial lag W_y in the endogenous variable y.

Now recalling the SLM: $y = \rho W y + X\beta + \epsilon$

Under the null hypothesis,

$H_0 : \rho = 0$

The standard regression, $y = X\lambda + \epsilon$ holds, whiles under the alternative hypothesis

$H_1 : \rho$ 6= 0 the extended regression model $y = \beta W y + X\beta + \epsilon$ would be valid.

For conducting the Lagrange multiplier test for only the spatial lag dependence (LM lag test) again only the standard regression model (OLS) is to be estimated. The statistics are simple LM_{Lag} test for a missing spatially lag dependence variable.

Test statistic:

$$LM_{Lag} = \frac{(e^T W y)}{nJ} \tag{3.49}$$

With $nJ = T + \dfrac{((WX\beta)^T M(WX\beta))}{S^2}$

M is the projection matrix

The test statistic is distributed as chi - square with one degree of freedom.

Critical value (significance level α): chi- squared ($1;1 - \alpha$)

Test decision:

$LM_{Lag} >$ chi - squared ($1;1 - \alpha$) ,Reject H_0

LM_{Lag} pertains to Spatial Lag model as alternative to OLS if it is statistically significant at a given level of significance (α)

3.12.4 Robust Lagrange Multiplier Tests for Errors

The Robust LM_{err} test for error dependence in the possible presence of a missing lag dependence variable. Anselin and Florax's Lagrange Test on errors, robust to presence of the Ignored Spatial Lag is given as (Yrigoyen, 2007):

$$LM - LE = \frac{[\frac{(e^TWy}{S^2} - \frac{(e^TWe)}{S^2}]^2}{(nJ) - T} \qquad (3.50)$$

The test statistic is distributed as chi- square with one degree of freedom The null and alternative hypothesis is set up as before:

$H_0 : \rho = 0$

$H_1 : \rho$ 6= 0

If the robust lag is significant then it implies that when error dependence variable is present the spatial lag dependent variable disappears, pointing at SLM as a preferred alternative.

3.12.5 Lagrange Multiplier SARMA test

The last test of Lagrange multiplier, LM - SARMA, relates to the higher order alternative of a model with both spatial lag and spatial error terms. More specifically, in addition to detecting the higher order alternative for which it is designed, the test also has high power against the one - directional alternatives. In other words, it will tend to be significant when either the error or the lag model is the proper alternatives, but not necessarily the higher order alternative (Anselin, 2005).

Anselin's Lagrange Multiplier SARMA test statistic is given as (Yrigoyen 2007):

$$SARMA = \frac{[\frac{(e^TWy}{S^2} - \frac{(e^TWe)}{S^2}]^2}{(nJ) - T} + \frac{[\frac{e^TWe}{S_2}]^2}{T} \qquad (3.51)$$

It follows a chi - squared distribution with two degree of freedom. It is only valid in linear models under the assumption of normality in errors.

The null and alternative hypothesis is given as:

$H^0 : \lambda = 0; \rho = 0$

$H_1 : \lambda \neq; \rho \neq 0$

3.13 Diagnostics Procedures

3.13.1 Multicollinearity condition number Test

Multicollinearity number is the square root of the ratio of the largest to the smallest Eigen value of the matrix $X^T X$, after row standardization (each row sums to 1) (Yrigoyen, 2007). Multicollinearity condition number test is not a test statistic per se, but a diagnostic to suggest problems with the stability of the regression results due to multicollinearity (the explanatory variables are too correlated and provide insufficient separate information). Typically, an indicator over 30 is suggestive of problems (Anselin, 2005). Also, a total lack of multicollinearity yields a condition number of 1 (Yrigoyen, 2007).

According to Yrigoyen (2007), the consequences of multicollinearity exceeding the threshold value of 30 is that, though OLS estimates are still BLUE, the standard error estimate of the regression coefficient will be misleading. The t - student value and/or the regression coefficients will be changing signs, leading to inaccurate conclusions. Yrigoyen suggested the following solutions to multicollinearity problems.

1. applying Principal Components or other synthesis method
2. considering extra-sample data
3. changing the model

3.13.2 Normality of the Errors Test

Jarque - Bera test which is used to test for the normality of errors is an asymptotic discrepancy test. The test statistic for Jarque - Bera test is given as (Yrigoyen 2007):

$$JB = \frac{(n-k)}{6}[S^2 + \frac{1}{4}(k-3)^2] \tag{3.52}$$

Where S is the skewness and K is the Kurtosis. The test statistic follows a chi squared distribution with two degree of freedom.

Sample skewness gives a measure of how symmetric the observations are about the mean. For a normal distribution skewness is 0. S is defined for a data set of errors $e_1, e_2, \ldots, e_n$:

$$S = \frac{\frac{1}{n}\sum_{i=1}^{n}(e_i - \hat{e})^2}{(\sigma^2)^{\frac{3}{2}}} \tag{3.53}$$

The sample Kurtosis gives a measure of the thickness in terms of probability density function. For a normal distribution, kurtosis is 3 and Excess kurtosis (EK) is given as:

$$EK = K - 3 \tag{3.54}$$

For a normal distribution, the EK is 0, that is $K - 3 = 0$
K is defined for a data set of errors $e_1, e_2, \ldots, e_n$ as :

$$S = \frac{\frac{1}{n}\sum_{i=1}^{n}(e_i - \hat{e})^4}{(\sigma^2)^2} \tag{3.55}$$

The Jarque - Bera test for normality is now presented. Consider testing the null hypothesis:

H_0 : the residuals are normally distributed, skewness is zero and excess kurtosis is zero;

H_1 the residuals are non - normal distributed

The null hypothesis of normality is rejected if the calculated test statistic exceed a critical value chi - square $(2;1-\alpha)$ distribution.

According to Yrigoyen (2007), most hypothesis tests and a large number of regression diagnostics such as MLE, F - test, t-students, Lagrange Multiplier test are based on the assumptions of normal distribution, hence non - normality of errors distribution will compromise these results. However, Anselin (2005) explain that, non - normality distributions of the errors may not be too serious a problem, since many properties in regression analysis hold asymptotically even without assuming normality. He, however, concluded that, for finite sample (or exact) inference, normality is essential.

Yrigoyen suggested using log transformation or any other Box - Cox variable transformation to correct this problem.

3.14 Tests for Heteroskedasticity of Errors

Heteroskedasticity refers to a situation where regression disturbances do not have a constant variance overall observations (that is, it is not homoskedastic). Some of the possible causes of heteroskedasticity in spatial data analysis are (Yrigoyen,

2007):

1. When there are systematic regional differences in the relationships youmodel (that is spatial regimes)
2. When using data for irregular spatial units (with different areas)

The consequences of ignoring heteroskedasticity when it is present, according to Yrigoyen, are:

1. The standard regression model will be misspecified.
2. The inference based on the usual t - test and F- test will be wrong
3. R -square measures of goodness - of - fit will be wrong (based on e^Te instead of $e^T\Omega^{-1}e$

The statistical tests performed to test for heteroskedasticity are the BreuschPagan test, Koenker - Bassett test and White test. Both the Breusch - Pagan and Koenker - Bassett tests are implemented as tests on random coefficients, which assume a specific functional form for the heteroskedasticity. The KoenkerBassett test is essentially the same as the Breusch - Pagan test, except that the residuals are studentized, i.e.,they are made robust to non - normality (Anselin, 2005).

The White test is a so - called specification robust test for heteroskedasticity, in that it does not assume a specific functional form for the heteroskedasticity. Instead, it approximates a large range of possibilities by all square powers and cross-products of the explanatory variables in the model. In some instances, this creates a problem when a cross-product is already included as an interaction term in the model (Anselin, 2005).

The null and alternative hypothesis of the test of heteroskedasticity is:

H_0 : the error variances are all equal against the alternative hypothesis;

H_1 : the error variances are a multiplicative function of one or more variables

3.15 Model Specification

According to Anselin (2005) while it is tempting to focus on traditional measures, such as the R2 in measuring the best fit of the model, this is not appropriate in a spatial regression model. The value listed in the spatial lag output is not a real R^2, but a so-called pseudo - R^2, which is not directly comparable with the measure given for OLS results.

Anselin stated that the proper measures of fit are the Log - Likelihood, the Akaike Information Criterion (AIC) and Schwarz Criterion (SC), also known as Bayesian Information Criterion (BIC). These three measures are based on an assumption of multivariate normality and the corresponding likelihood function for the standard regression model. The higher the log - likelihood, the better the fit (high on the real line, so less negative is better). For the information criteria, the direction is opposite, and the lower the measure, the better the fit.

According to Zhu and Chi (2010), Akaike's Information Criterion (AIC) and Schwartz's Bayesian Information Criterion (BIC) measure the fit of the model to the data but penalize models that are overly complex. Models having a smaller AIC or a smaller BIC are considered the better models in the sense of model fitting balanced with model parsimony.

The mathematical relation between the three information criterions is shown below:

The $AIC = -2L + 2K$,

where L is the log - likelihood and K is the number of parameters

The $SC = -2L + Kln(n)$,

where ln is the natural logarithm.

Hence the model with the highest Log likelihood and the lowest measures of AIC and BIC will be considered as the best measure of fit to the data.

Chapter 4

Results and Analysis of Data

4.1 Introduction

This session entails, the presentation of results on the analysis of data.

4.1.1 Exploratory Spatial Data Analysis (ESDA)

This section gives preliminary analysis of the data and involves exploratory of the data by means of summary statistics, charts, graphs and PCA are presented. The statistical Software used in this analysis is SPSS 20 and the spatial regression software used is GeoDa 1.6.2.

Table 4.1: Wealth Median Factor Scores

Characteristic	Value
Mean	0.0129577
Median	-6.78×10^{-2}
Mode	0.78970
Skewness	0.392
Std. Error of skewness	0.120
Kurtosis	-0.491
Std. Error of Kurtosis	0.240
Minimum	-1.49636
Maximum	3.22193

Table 4.1 above shows both the skewness and kurtosis of the median wealth factor scores of the women, the dependent variable, wealth median factor scores. It is clear from the results that the distribution of the dependent variable satisfies the criteria of a normal distribution.

The skewness (0.392) and kurtosis (-0.491) were both between -1.0 and +1.0. Therefore analysis was carried out without any further transformation of the DV, median wealth factor scores.

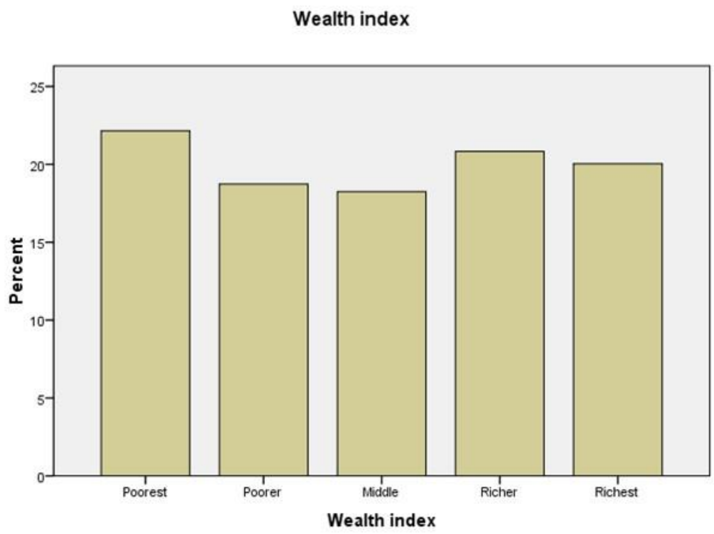

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Figure 4.1: Wealth Index

4.1.2 Women Poverty Compares With the Overall National Poverty

The above graph shows percentages of Ghanaian women that fall into each national wealth quintile. It is clear from the graph that the distribution of the respondents' (women) wealth is more missed. There is a slightly disproportionately large percentage (22%) in the lowest bottom quintile (poorest). The second bottom and middle quintiles are both less than 20%, these two quintiles are slightly under represented. However, the upper two quintiles are fairly proportionate (almost 20%). It is interesting to note that the bottom two quintiles (poorest and poorer) represent 40.9% of the total respondents and the upper two quintiles (richer and richest) also represent 40.8%.

From these results it can be concluded that women poverty is not much different from the overall poverty status in Ghana.

4.1.3 Selecting Uncorrelated Independent Variables Using PCA

Using PCA, nine components were extracted from a group of 27 socio - economic and demographic variables which explained more than 73% of the common variance in the model, PCAs. The selection of the uncorrelated independent variables was based on high loadings of Varimax of the rotated principal components to obtain the subset of the IV to be used in the spatial econometric model. The results are shown in the table 4.2 below.

Table 4.2: Extraction Sum of Squared Loading

Components	Total	% of Variance	Cumulative
1	7.840	29.036	29.036
2	2.771	10.262	39.298
3	1.924	7.128	46.426
4	1.524	5.643	52.069
5	1.310	4.850	56.919
6	1.183	4.383	61.302
7	1.122	4.158	65.458
8	1.038	3.845	69.303
9	1.011	3.745	73.048

The IV selected were grouped as Marital Status, MS [Married (MS - M), Divorce(MS- D), Not living together (MS - NLT)], Occupation, OCC [Service (OCC - SVC), Agric (OCC - AGR), Clerical (OCC - CLRC), Skilled Manual (OCC - SM), Unskilled Manual (OCC- USKL)], Education, ED [No education (ED - NO), Primary (ED - PR), Higher (ED - HI)], Demographic [Parity and Average household size (AHSz)] and Headship , HH [Female headed households (HH - FH)]

4.1.4 Global Moran's I

An ESDA descriptive measure for the response variable (wealth factor score) is performed.

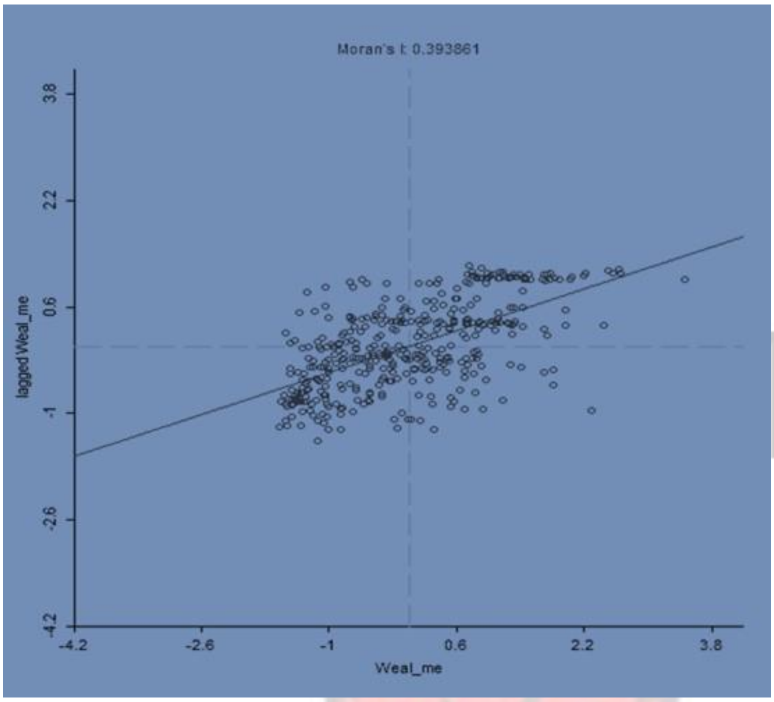

Figure 4.2: ESDA for Moran's Scatter Plots

The Moran's scatter plot of wealth factor scores is shown in Figure 4.2. The Moran's I for the WMFS is 0.394 and has indicates the presence of spatial dependence in the data. This suggests a clustered spatial pattern of the distribution of poverty in the women's WMFS. The p-value for the observed Moran's I statistic is 0.001, indicating that the likelihood of the observed clustered pattern of poverty being a result of random chance is less than 1 thousand (Higazi et al., 2013). Also, the value Moran's I statistic (0.394) indicates that poverty among women in Ghana is spatially distributed in clusters. This result is compatible with the visual images of the spatial distribution of WFS depicted in Figure 4 below. Further, the implication of diffusion across space suggests that, for a given cluster, as poverty in neighbouring areas increases, the likelihood of its poverty rates increases as well.

The upper right quadrant of the Moran scatter plot shows those clusters with above average wealth factor scores and are neighbours of above average wealth factor scores by a combination of high - high (i.e. wealthy clusters surrounded by wealthy clusters). These clusters are “cold spots ”poverty areas (higher wealth means lower level of poverty). In other words, the incidence of poverty in these areas is very small. Also, the lower left quadrant shows clusters with below average wealth factor score values and are neighbours with below average values clusters by a combination of low - low (i.e., poor clusters surrounded by poor clusters). These areas are “hot spots ”of poverty (lower wealth means higher level of poverty). Both regimes (LL and HH) have a positive partial association and they represent what Anselin (2005) referred to as spatial clusters. The lower right quadrant displays clusters with above average wealth factor scores surrounded by clusters with below average values by a combinations of high-low (i.e., wealthy clusters surrounded by poor clusters), and the upper left quadrant contains the opposite (low - high). The LH and the HL scheme exhibits an atypical negative spatial association (spatial outliers) and scattered around the country.

The exploration of figure 4.2 which is aided by “linking and brushing ”(one of the accessible ESDA functionality in the GeoDa software), has specified that high high clusters are mainly in southern areas and the major cities (such as Accra, Kumasi and Sekondi), whereas low -low Clusters are mainly in the northern part of the country and other rural areas. Most of the low - high clusters are neighbors of the areas identified as cold -spot, whereas high aˆ low clusters are neighbours of hot - spot of poverty.

4.1.5 Local Moran’s I (LISA Map)

The Global Moran’s I statistic summarizes the nationwide spatial dependence with a single statistic (0.394). However, this global or nationwide statistic does not tell us where the poverty clusters might be, but rather only proposes that the spatial pattern of poverty that we detect is not by chance or random; there is more similarity by location than one would have been expected if the pattern were by chance or random.

A map of the “local ”Moran’s I statistic for our dependent variable, a LISA map

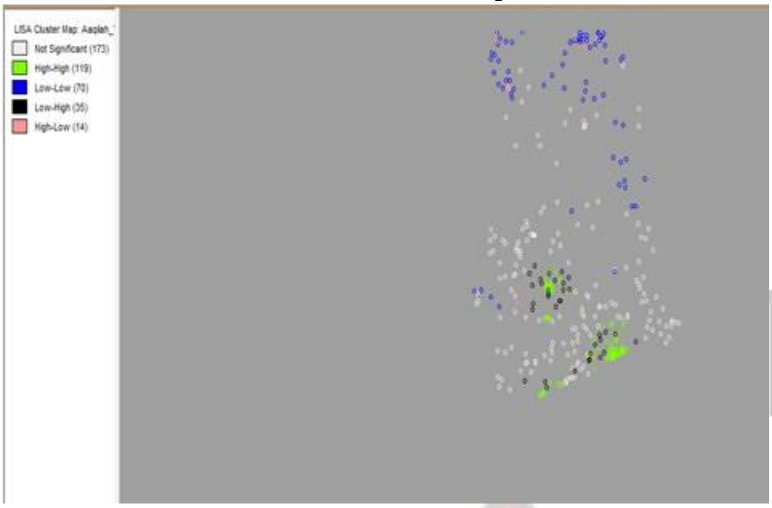

Figure 4.3: LISA Map of Wealth Factor scores

(for Local Indicators of Spatial Association), provides further evidence for the Moran scatterplot by displaying the same data, MWFS in a different way (Figures 4.3). The LISA map shows the geographic distribution of the various value combinations (high-high, low-low, low-high, high-low in Figure 4.3) for all 411 clusters across Ghana. Clusters where the local Moran statistic is not significant (at the 0.05 level, based on a randomization procedure) are not shaded on the map.

Figure 4.3 revealed significant and stark patterns of poverty among women in Ghana. A peculiar north south discrimination of high versus low poverty concentrations was found. This pattern can be described as following a continental poverty divide. The insight of the pattern can be very useful in explaining the underlying processes involved in forming such spatial patterns that result in concentrated high poverty rates in some areas and low poverty rates in other areas. Cold spots of poverty include 119 (30.0%) of HH (lawn green) clusters of southern cities, including Accra, Kumasi and Sekondi, which are already identified in fig. 1 above. Also, a band of LL (dark blue) Clusters of 70 (17.0%) stretches northwards from Brong Ahafo region to the northern parts of the country, indicating hot spots of poverty areas. A few statistically significant (at the 0.05 level) low

- high clusters 35 (8.5%) are adjacent to the major southern cities which were identified earlier as cold spots of poverty. Further, individual high - low clusters 14(3.4%) are neighbours of cold - spot (poverty - poverty) clusters and scatter throughout the three northern regions, perhaps indicating metros or sub - metros in these areas.

While this exploratory assessment of the data may suggest hypotheses to test in further analysis, the foremost message is that, taken together, the maps in Figure 1 and Figures 2 confirm that women poverty is a highly clustered regional phenomenon.

4.1.6 Global and Local Moran's I of One of The Predictors - Parity

The map and scatter plot below highlight the spatial dependency of one of the explanatory variables, parity; the average number of children given birth to per cluster. From the diagram, the Moran's I is 0.16822 (p < 0.001). The highly significant Moran's I indicate that parity is one of the Geographical determinants of poverty. Hence, the number of children a woman will give birth to is highly influenced by the number of children of her neighbours.

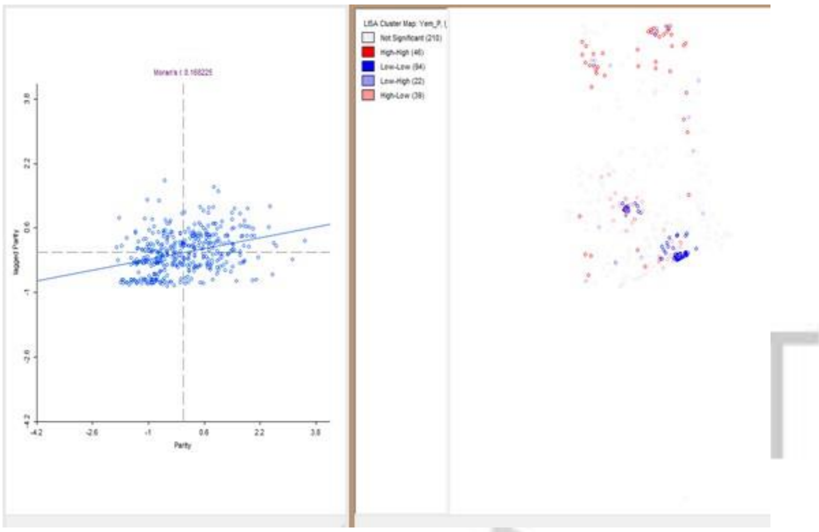

Figure 4.4: Moran's I and LISA Plots

Figure 4.4 above depicts very contrasting results to LISA map of the response variable in figure 4.3 Interestingly, from the two diagrams, the low - low clustered areas of wealth factor scores in Figure 4.3 turned to have high - high of parity clusters in Figure 4.4. This implies that the number of children a woman gives birth to greatly affects her poverty status. The northern part of Ghana which appears to be home to concentrated clusters of low - low wealth turned to clusters of high - high parity clusters. Also, the southern part of Ghana with concentrated clusters of wealth (high - high) turned to low-low clusters of parity. Hence there is an inverse relation between wealth and parity. That is, the higher the parity, the more likely of falling into poverty.

The Moran's I and z - values of each independent variable is shown in table 4.3 below.

Table 4.3: Moran I for each explanatory Variable

Variable	Moran's	z - value	Variable	Moran's I	z - value
Parity	0.168	9.099	OCC-SVC	0.089	5.144
HH-FM	0.152	8.303	OCC - SKL	0.085	4.606
AHSz	0.287	13.233	OCC - USKM	0.085	4.600
MS-NLT	0.039	3.313	OCC - CLR	0.073	3.805
ED-NO	0.353	18.849	OCC - AGR	0.0251	13.208
ED - PR	0.116	6.539	MS-MRD	0.426	23.546

ED - HI	0.063	5.144	MS-DVC	0.0162	1.074

Table 4.3 displays the Moran's I statistic of all the variables. Inference is based on a standardized z-value that follows a normal distribution. All the variables are positively spatially auto correlated except Ms - DVC. Also, each variable has a p-value of 0.001 bar ED - HI (0.01), MS - DVC (0.988), MS - NLT (0.038), and OCC - CLR (0.003). Because, Moran's I is similar (but not equal) to a correlation coefficient, we could possibly reason that the variables show different intensities of spatial associations. This is higher for the variables ED -NO, AHSz, HH -FM, MS -MRD, ED-PRM, and OCC -AGR. The other variable such as ED - HI and OCC - CLR command lower values of Moran's I.

The high intensities of the global association index (Moran's I) of these variables indicate a tendency towards geographical clustering of similar clusters with a high (or low) value of the variable (e.g. clusters with high or low value of AHSz are geographically clustered). Conversely, the low positive value of Moran's I with regard to the variables ED-HI and OCC -CLR could indicate a non-geographical clustering of similar clusters; i.e. the low value of Moran's I indicates lack of similarity among ED-HI and OCC-CLR.

4.1.7 Using Residual Map to Check Over and Under Prediction of Poverty

Figure 4.5 below shows the residual map and scatter plot of residuals which are useful for a visual inspection of patterns of the residuals.

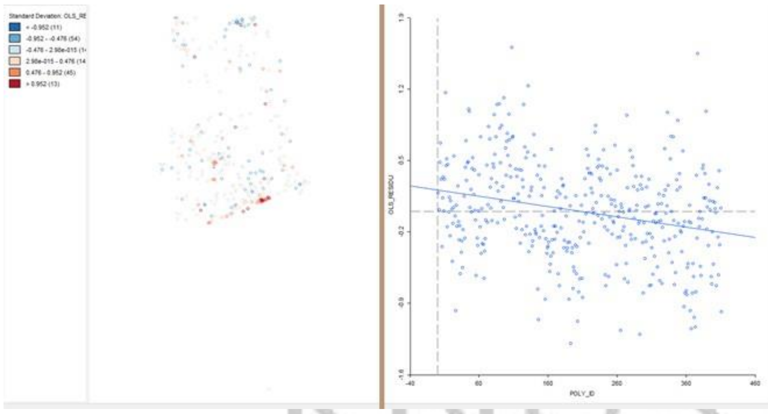

Figure 4.5: Residual plots

On the residual map in Figure 4.5, the dark red clusters are positive residuals. Positive residuals (under-predictions of wealth), means the rate of poverty in these areas are much lower than what the OLS model predicts. From inspection, the dark red clusters corresponds to high -high clusters in the WFS mappings in Figure 4.2. This implies that the poverty in these areas is much lower than what the model predicts. Also, the negative residuals indicate over - predictions of wealth. On the residual map in Figure 4.3, these clusters are dark blue, which means the rate of poverty in these areas are much higher than the OLS model predicts. Interestingly, these areas correspond to low - low clusters in the WFS mappings in Figure 4.2. This implies that the rate of women poverty in the northern part of the country is much higher than what OLS is predicted.

This map does suggest that similarly coloured areas tend to be in similar locations, which could indicate positive spatial autocorrelation. This is confirmed by a Moran's I test for residual spatial autocorrelation which is found to be positive and highly significant (Moran's I is 0.1682; $p < 0.001$). Also ,Figure 4.5 highlights both positive and negative large residuals. These large residuals seem to be scattered across the graph, these large residuals in the plot are constrain to be less than ±2 indicating that they do not warrant further investigations or removal to improve the performance of the model.

4.1.8 Detecting heteroskedasticity: Residuals vs Predicted values

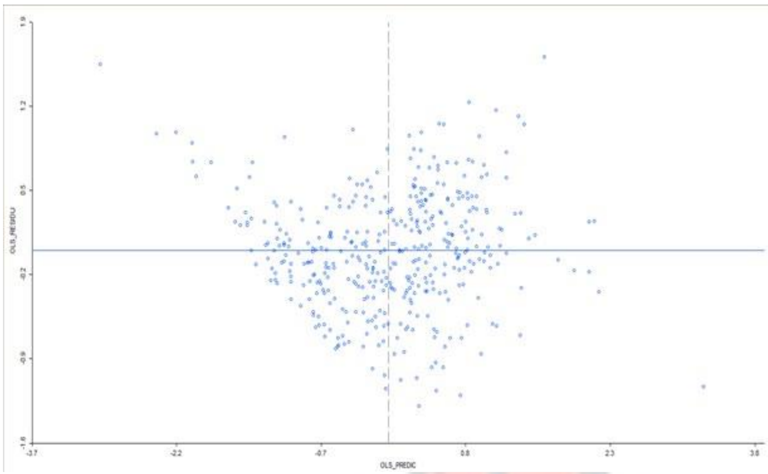

Figure 4.6: The Scatter Plot of OLS Residuals against Predicted Values

From Figure 4.6 above, the scatter plot exhibit a funnel - like pattern. This indicates non - uniform predictions of wealth factor scores across various clusters and the possibility of the presence of non - constant variance - heteroskedasticity. Also, the straight line that runs diagonally across the bottom of the graph indicates the clusters with zero rates of wealth factor scores. Selecting these points and observing them in the table has shown that all the ten regions in Ghana have at least one of such clusters with a wealth factor score of zero except Greater Accra and Volta Region. These clusters cannot be described as either poor or wealthy clusters. They could be said to be in equilibrium state of their socio economic status or wellbeing.

4.1.9 The Effect after Including the Spatial Autoregressive Error Term

Figure 4.7 contains Moan's I scatter plots, the model residuals (ERR - RESIDU), the predicted values (ERR - PREDIC), and the prediction error (ERR-PRDERR). Residuals and prediction error could be used to evaluate the effect of SLM after including spatial error. The results in Fig 8 revealed an insignificance Moran's I (Moran's I = −0.0054; p = *value* < 0.474). This clearly reflects lack of correlation, which means including the spatial autoregressive error term could have eliminated all spatial effects from the model. This is only exploratory and further test is needed to confirm this.

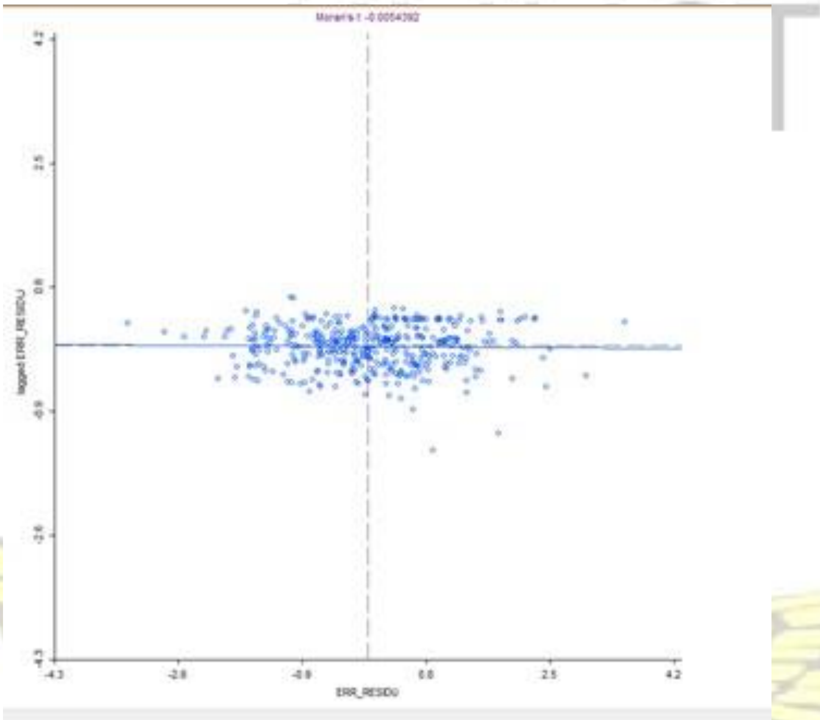

Figure 4.7: Moran scatter plot for Spatial Error Model Residuals

4.1.10 The Effect after Including the Spatial Autoregressive Lag Term

Figure 4.8 contains Moran's I scatter plots, the model residuals (LAG-RESIDU), the predicted values (LAG - PREDIC), and the prediction error (LAG-PRDERR). Residuals and prediction error could be used to evaluate the effect of SLM after conditioning the Lag effect. The results in Fig 9 revealed an insignificant Moran's I (Moran's (I) = 0.0249;p − *value* < 0.070). This clearly reflects lack of correlation, which means including the spatial autoregressive lag term could have eliminated all spatial effects from the model, this is only exploratory and further test is needed to confirm this.

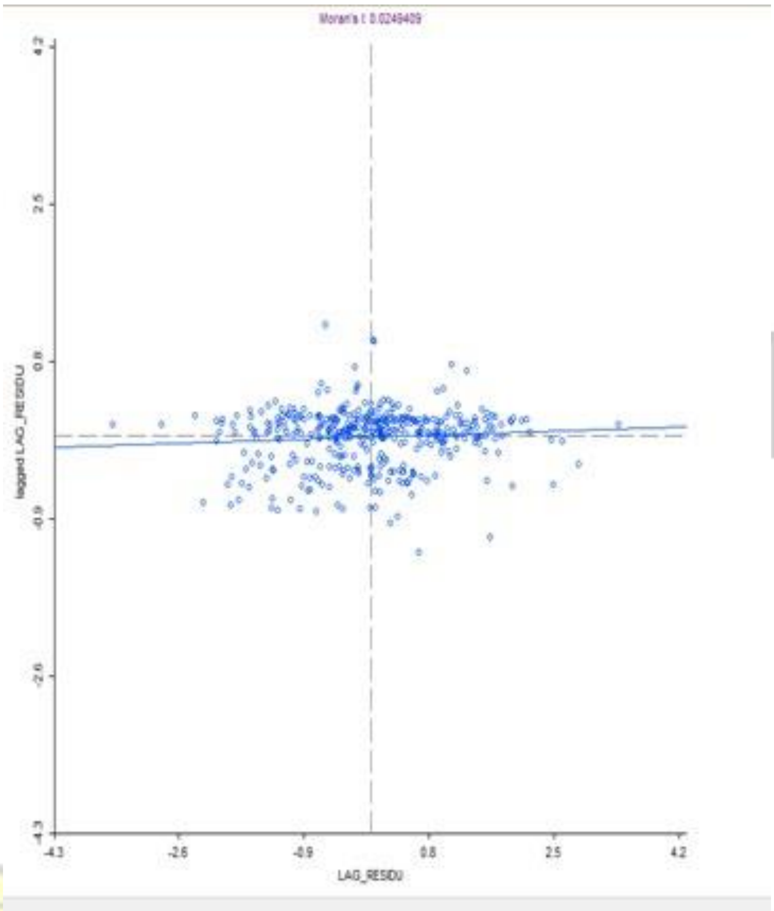

Figure 4.8: Moran scatter plot for Spatial Lag Model Residuals

4.2 Confirmatory Spatial Data Analysis

A classical regression was performed first to model the functional relationship between cluster level of women poverty and the spatial independent variables. Three different analyses were performed: First, Ordinary Least Squares (OLS) regression is performed as a reference model; secondly, estimation by means of maximum likelihood of a spatial regression model that includes a spatially lagged dependent variable, and lastly, estimation by means of maximum likelihood of a spatial regression model that includes a spatially lagged error.

4.2.1 Ordinary Least Square Regression

Table 4.4: Summary Output of OLS Estimation

Summary	value

R - Squared	0.74797
Adj. R - Squared	0.73971
S.E of Regression	0.47528
F - Statistic	0.0000
Log Likelihood	-270.346
Akaike inform. criterion	568.691
Schwarz Criterion	624.9520

In the OLS model the adjusted R-square is 0.748; this implies that about 74.80% of the variations in the median wealth factor scores (MWFS) are explained by the model. Without accounting for the spatial dependence detected in the data, OLS explains a considerable portion of the variation in the dependent variable. This is probably due to strong linear relation between the DV and the IVs used in the model and also an indication of the absence of many influential outliers in the data as suggested earlier.

The results of F test for the OLS models is high (F = 90.6302), rejecting the null hypothesis that the explanatory variables are jointly not significant to capture the variation of the MWFS.

Table 4.5 show a summary statistics of IVs including SE, p - values and regression coefficient associated with each variable in the model.

Table 4.5: OLS Model

Variable	Co - efficient	Std.Error	t- Statistic	Prob.
Constant	0.86756	0.13002	6.6725	0.0000
ED- NO	-0.061375	0.012403	- 4.948605	0.0000
ED-PR	- 0.0342005	0.014917	- 2.292684	0.02239
ED-HI	0.22099	0.0275513	8.021065	0.0000
OCC-NW	0.004020	0.014343	0.280315	0.77938
OCC- CLRC	0.13000	0.062483	2.08061	0.03811
OCC - AGR	-0.09411	0.01108	-8.49221	0.0000
0CC- SVC	0.048642	0.022283	2.18303	0.02962
0CC - USK	-0.047259	0.022340	- 2.115412	0.03502

MS- MRD	0.027676	0.01182	2.341456	0.01970
MS - NLT	0.0064909	0.036602	0.177340	0.85933
Parity	-0.220176	0.0359035	- 6.132451	0.0000
AHSZ	-0.002256	0.020323	-0.11101	0.91164
HH - FM	-0.006079	0.010017	- 0.606852	0.54429

From table 4.5, using 5% significance level, it is clear that all the Education and Occupation related variables are significant (except OCC - NW) with mixed effects on women poverty. On the other hand, ED - NO and ED - PR negatively affect women's wealth (due negative coefficient of β) and thereby increase the chances of a woman falling into poverty. ED - HI has an opposite effect. Thus, for education, women poverty will be reducing significantly as the educational level of women increases from ED - NO (-0.061), ED - PR (-0.034), and ED - HI
(0.221). Also, For Occupation, considering the sign of their coefficients, OCC CLR (0.130) and OCC-SVC (0.049) decreases the likelihood of a woman falling into poverty whiles OCC - USK (-0.094) and OCC - ARG (- 0.047) rather increase the likelihood of a woman becoming poor. For marital status, only MS - MRD
($p - value < 0.01970$) is significant with decreasing chances of becoming poorer. Parity, which is highly significant ($p - value = 0.00000$), has the worst effect of a woman's wealth ($\beta = -0.220$); that is parity is the largest contributory factor to a woman becoming poorer among all the IVs employed in the OLS model.

However, OLS model does not produce enough statistical evidence on the effect of AHSz, OCC - NW, MS - NLT, and HH - FML on women poverty.

4.3 OLS Regression Diagnostic

The first set of diagnostics provided in the regression output 1 consists of three traditional measures: the multicollinearity condition number, a test for nonnormality (Jarque -Bera), and three diagnostics for heteroskedasticity (Breusch Pagan, Koenker -Bassett, and White). The result is shown below.

4.3.1 Test for Heteroskedasticity

Table 4.6: Diagnostics for Heteroskedasticity

Test	Df	Value	Prob.
Breusch - Pagan test	13	52.0909	0.00000
Koenker - Bassett test	13	46.4506	0.00001
White	104	203.8266	0.00000

H_0 : the error variances are all equal;

H_1 : the error variances are a multiplicative function of one or more variables.

From the result above, Breusch - Pagan test ($p - value$ = 0.00000), Koenker Bassette (0.00001) and White tests (0.00000) are all statistically significant indicating that the null hypothesis should be rejected. These results have clearly revealed heterogeneity of error variance; that is the error terms do not have constant variance, clearly violating one of the conditions of OLS. This result is not surprising, considering the non-stationarity associated with HL and LH detected in the ESDA.

Multicollinearity Condition

The Multicollinearity Condition number (18.958686) is not a test statistic but a diagnostic test to detect the stability of the regression result due to correlation among IVs. Diagnostic tests for OLS results in Table 4.6 showed that multicollinearity is not bordering the OLS model since the number (18.956) is less than 30 according to the conditional number of Anselin (2005). This implies that the model contains no redundant variables; that is all the IVs are offering sufficient separate information of accounting for the variations on women poverty.

Test of Normality of Errors

Table 4.7: Normality of Errors Test

Test	Df	Value	Prob.
Jarque - Bera	2	2.1663	0.33853

H_0 : the residuals are normally distributed, skewness is zero and excess kurtosis is zero;

H_1 : the residuals are non - normal distributed.

From the results, Jarque - Bera test statistic is 2.1663 with p - value as 0.33853. This reveals a highly insignificant statistical test. This implies that the test failed to produce substantial evidence against H_0, hence failure to reject H0. Thus, the errors are normally distributed, establishing non-violation of one of the conditions of OLS. This result indicates that the model might have captured all the important IV needed to determine the possible causes of women poverty.

4.3.2 Further Test for Spatial Dependence

The final collection of model diagnostics consists of six tests performed to assess the spatial dependence of the model. These include Moran's I and six Lagrange Multiplier. The first two (LM-Lag and Robust LM - Lag) pertain to the spatial lag model as the alternative to OLS. The next two (LM - Error and Robust LM - Error) refer to the spatial error model as the alternative. The last test, LMSARMA, relates to the higher order alternative of a model with both spatial lag and spatial error terms.

Table 4.8: Diagnostics for Spatial Dependence

Test	MI/Df	Value	Prob.
Moran's I (error)	0.1617	9.2287	0.00000
Lagrange Multiplier (lag)	1	95.6850	0.00000
Robust LM (lag)	1	46.0666	0.00000
Lagrange Multiplier (error)	1	71.8547	0.00000
Robust LM (error)	1	22.2363	0.00000
Lagrange Multiplier (SARMA)	2	117.9212	0.00000

Test for Spatial Dependence of the Residuals: Moran's I

H_0 :there is no spatial autocorrelation of the residuals

H_1 : there is a spatial autocorrelation of the residuals

Moran's I Score of 0.1617 is highly significant (p - value = 0.0000) indicating that the null Hypothesis should be rejected. This implies that there is a strong spatial autocorrelation of the residuals. The Moran's I test on the residuals after fitting the standard linear regression suggests that there is strong evidence of spatial autocorrelation among the residuals ($Moran^{0}sI = 0.1617; p - value < 0.0000$). Thus the independence assumption of the error term appears to be violated and hence the need to use spatial linear regression models in order to account for the spatial autocorrelation detected.

Lagrange Multiplier Test for Spatial Error Dependence

H_0 : spatial error autoregressive coefficient (λ) is equal to zero

H_1 : spatial error autoregressive coefficient (λ) is not equal to zero

From the output, the LM_{ERR} value is 71.8547 with p - value of 0.0000, indicating a high significant test. This called for rejection of H_0 of zero spatial autocorrelation; hence there is a presence of spatial autocorrelation of residuals (error spatial dependency). The significance test suggests SEM as a better alternative.

Lagrange Multiplier Test for Spatial Lag Dependence H_0 :

spatial Lag autoregressive coefficient ρ is equal to zero.

H_1 : spatial Lag autoregressive coefficient ρ is not equal to zero.

From the output, theLM_{LAG} value is 95.685 with p - value of 0.0000, indicating a high significant test. This called for rejection of H0 of zero spatial autocorrelation; hence there is a presence of Lag spatial dependency and pointing to SLM as better alternative. This implies that the rate of poverty in one area is highly influenced by poverty rate in the neighboring areas. According to this model, poor regions or poverty endemic areas will be considered as poverty traps.

Robust Lagrange Multiplier Test for Error Dependence

$H_0 : \lambda = 0$

$H_1 : \lambda\ 6= 0$

The robust Lagrange multiplier value for error is 22.2363 with p - value of 0.0000 indicating a high significant test. This implies that when the wealth factor score of neighbouring clusters is present (Lag dependent variable); the spatial autocorrelation among the residuals (error dependence) disappears suggesting SEM as a preferred alternative.

Robust Lagrange Multiplier Test for Lag Dependence

$H_0 : \rho = 0$

$H_1 : \rho\ 6= 0$

The robust Lagrange multiplier statistic for Lag is 46.0666 with p - value of 0.0000, indicating a high significant test. This implies that the presence of error dependence has made the Lag dependent variables disappear, suggesting SLM as a preferred alternative.

Lagrange Multiplier SARMA Test for spatial Dependence

$H_0 : \rho;\lambda = 0$

$H_1 : \rho\ 6=;\lambda\ 6= 0$

The LM - SARMA test is highly significant ($LM - SARMA$ = 117.9212;$p - value$ = 0.0000) indicating that either the error or the lag model is the proper alternative to OLS (Aselin 2005).

The analysis of OLS output indicates that the errors were normally distributed but the constant variance condition is violated and that the spatially dependence detected earlier really exist as confirmed by the entire five significant test conducted. These results clearly showed that spatial econometric models will fit the data better than OLS. However, both simple LM and robust LM failed to indicate the best alternative model.

4.3.3 Spatial Error Model and Spatial Lag Model

After identifying the presence of spatial dependence, we proceeded to re-estimate the model with maximum likelihood approach while controlling for spatial dependence. In particular, since the five dependence tests failed to establish which model is the best alternative to OLS.

Spatial Lag Model

This model evaluates the strength spatial relations of WFS among neibouring clusters

Table 4.9: MLE of the Spatial Lag Model

Summary	value
R -Squared	0.791524
Sigma Square	0.180493
S.E of Regression	0.424845
Lag Coeff.(Rho)	0.374779
Log Likelihood	-233.779
Akaike inform. criterion	497.557
Schwarz Criterion	557.836

From the output, the fit of the model improve with the inclusion of the indicators of spatial dependence in the model; R-squared increased from 74.80% to 79.10% and S.E of regression also reduced marginally from 0.475288 to 0.424845 indicating that the SLM better explains the variance of the women poverty than OLS. Also, unlike OLS results, the SLM, after accounting for the lag dependence were able to detect two additional insignificant Occupation variables, OCC CLRC and OCC - SVC. However, the remaining variables were still statistically significant with the expected signs after including spatial Lag term. Another remarkable feature observed between OLS and SLM is that OLS were under estimating the coefficient of statistically significant variables. For example, in ED - NO, $\beta_{OLS} = -0.037188$ changed to $\beta_{Lag} = -0.03420045$ and for ED- HI, $\beta_{OLS} = 0.2268892$ changed to $\beta_{Lag} = 0.2209904$. These reductions reflected across coefficients of all the variables, and give an indication that OLS were under predicting poverty in some areas.

Table 4.10: Spatial Lag Model (SLM)

Variable	Co -efficient	Std.Error	t- Statistic	Prob.
Constant	0.6422765	0.1187849	5.407056	0.00000
ED- NO	-0.03718831	0.01141314	-3.258376	0.00112
ED-PR	-0.03082662	0.01333635	-2.311473	0.02081
ED-HI	0.2268892	0.02462739	9.212878	0.00000
OCC-NW	0.0004547441	0.01282065	0.03546966	0.97171
OCC-CLRC	0.08307731	0.05599916	1.483546	0.13793
OCC - AGR	-0.09061953	0.009918415	-9.136494	0.00000
0CC-SVC	0.03565577	0.01993086	1.788973	0.07362
0CC - USK	-0.04451582	0.01997153	-2.228964	0.02582
MS- M	0.03280628	0.01057288	3.102869	0.00192
MS - NLT	0.01509319	0.03273128	0.4611243	0.64471
W-WMFS	0.3747793	0.04129351	9.075986	0.00000
AHSZ	0.0130481	0.01821502	0.7163376	0.47378
HH - FM	-0.003811574	0.008955362	-0.4256192	0.67039
Parity	-0.2085365	0.03212889	-6.490621	0.00000

The spatial Lag term of WFS appears as additional indicator. Its coefficient parameter (ρ = 0.4;0.0000) reflects the spatial dependence inherent in our sample data, measuring the average influence on poverty of respondents by the poverty of their neighbours. In other words, the positive value of ρ implies that poverty rate in cluster i is correlated with the poverty rate in other neighbouring clusters; that is clusters with high (or low) poverty rates are clustered together. The three information criterions which compare the best fit between OLS and SLM and penalize the overly complex model are shown in Table 4.6 below:

From Table 4.11, the MLL value (-233.779) of SLM is relatively larger than (on a

Table 4.11: Information Criterion for OLS and SLM

Model	OLS	SLM
Log likelihood	-270.346	-233.779
AIC	568.691	497.537
SC	624.952	557.83

real number line) that of OLS (-270.346) indicating that SLM fit the data better than OLS. Also, both AIC (497.537) and SC (557.836) of SLM are respectively much smaller than the AIC (568.691) and SC (624.952) of OLS further highlighting the improvement of SLM over OLS, since the smaller the values of AIC and

SC the better the fit. **Diagnostics for Heteroskedasticity**

Table 4.12: Heteroskedasticity test

Test	Df	Value	Prob
Breusch-Pagan test	13	29.9941	0.00472

On the regression diagnostic test in SLM output, the probability in BreuschPagan test has increased considerable (from 0.0000 to 0.00472) but it is still less than 0.05 suggesting that there is still heteroskedasticity bordering the model after introducing the spatial lag term.

Finally, the likelihood ratio test of spatial lag dependence which compares the OLS to SLM is given as:

$$LRT = 2Log(\frac{L_{Lag}}{L_{OLS}}) = 73.1338(p < 0.05)$$

This is a highly significant test (LRT value = 73.1338; p - value = 0.0000) indicating that even though the introduction of spatial lag term has improved the model fit, it however did not make the spatial effect go away completely as suggested in the exploratory analysis.

Diagnostics for Spatial Dependence

Table 4.13: Heteroskedasticity test

Test	Df	Value	Prob
Likelihood Ratio Test	1	73.1338	0.00000

Spatial Error Model

Table 4.14: MLE of the Spatial Error Model

Summary		value
R -Squared	0.790595	
Sigma Square	0.181297	
S.E of Regression	0.425795	
Lag Coeff.(Lambda (λ))		0.660871
Log Likelihood	-241.669968	
Akaike inform. criterion	511.34	
Schwarz Criterion	567.6	

The obtained R - square value for SEM is 79.10% which is almost equal to that of SLM (79.20%) indicating that both SLM and SEM explain the variance of the dependent variable (poverty) better than OLS. The lag coefficient $\lambda = 0.70$ is significant ($p < .05$). The coefficient of the spatially correlated errors ($\lambda 0.70; p < 0.05$) is added as additional indicator. It has positive effect and is highly significant. As a result, the general fit improves as indicated by higher values of R - square and log likelihood. Like the Lag model, the effect of other variables remains virtually the same. SEM also constrains OCC - CLRC and OCC - SVC as insignificant. Similar to the Lag model, the Heteroskedasticity test remains significant ($p < 0.05$). Also, the likelihood ratio test for the comparison of the SLM model to the OLS model is:

$$LRT = 2Log(\frac{L_{error}}{L_{OLS}}) = 60.59(p < 0.05)$$

The LRT of spatially error dependence has significant results (p < 0.05). Therefore, we conclude that although allowing the error terms to be spatially correlated improve the model fit, it did not make the spatially effect go away completely.

Table 4.15: SEM Model

Variable	Co -efficient	Std.Error	t- Statistic	Prob.
Constant	0.6834885	0.1338072	5.10801	0.00000
ED- NO	- 0.04380168	0.01279898	-3.422279	0.00062
ED-PR	- 0.03024075	0.01366841	-2.212456	0.02694
ED-HI	0.2315247	0.02495919	9.276131	0.00000
OCC-NW	- 0.005070131	0.01321487	- 0.3836686	0.70122
OCC-CLRC	0.07546922	0.05623304	1.34208	0.17957
OCC - AGR	-0.0882618	0.01022775	-8.629637	0.00000
0CC-SVC	0.02667495	0.02022234	1.319083	0.18714
0CC - USK	– 0.04418815	0.01996186	-2.213629	0.02685
MS- M	0.03279017	0.01118151	2.932535	0.00336
MS - NLT	0.01254188	0.03237733	0.3873663	0.69849
Parity	-0.2100817	0.0317153	-6.623987	0.00000
AHSZ	0.01339055	0.01802139	0.7430368	0.45746
HH - FM	- 0.002569544	0.009132316	- 0.2813683	0.77843
Lambda	0.6608713	0.06042257	10.93749	0.00000

Table 4.16: Heteroskedasticity test

Test	Df	Value	Prob
Breusch-Pagan test	13	34.1602	0.00114

Diagnostics for Spatial Dependence

Table 4.17: Heteroskedasticity test

Test	Df	Value	Prob
Likelihood Ratio Test	1	57.3513	0.00000

The information criterion obtained from SEM is compared to those obtained from OLS and SLM and the results is summarize in Table 3.

It is obvious from table 4.18 that the log likelihood of both SLM (-233.779) and SEM (-241.670) is much larger than that of OLS (-270.346) indicating that the spatial models fit the data better than OLS. The better of the fit of the data by Table 4.18: Information Criterion for OLS,SLM and SEM

Model	OLS	SLM	SEM
Log likelihood	-270.346	-233.779	-241.670
AIC	568.691	497.537	511.340
SC	624.952	557.83	567.600

the spatial models is further highlighted by the reduced values of AIC and SC of the spatial model compared to the OLS model. The AIC of SLM and SEM are 497.537 and 511.340 respectively, and they are both smaller than the AIC of OLS model (568.691). For SC, the SLM and SEM values are respectively 557.836 and 567.600 both of which smaller than that of OLS (629.952).

Now, comparing the two spatial models, it is clear from output 2 and 3 as well as table 3 that, SLM fit the data better than SEM. This is because apart from a slightly improved R-squared value, SLM has larger MLL value (-233.779) than SEM (-241.670). To further elucidate this point, there are much reduced values of both AIC (497.537) and SC (557.836) of SLM compare with AIC (511.340) and SC (567.600) of SEM.

Comparing the spatial lag and spatial error models to OLS, it is obvious that both alternative models yield improvement to the original OLS model. Therefore we could conclude that controlling spatial dependence will considerably improve our model performance.

4.4 Evaluation of Spatial Models

There are significant differences to be observed between the results obtained with

the OLS, SEM and SLM models (Table 4.5) and this may have an impact on decision making. This fact, once again emphasises the importance of taking spatial effects into account. Approaches not taking these spatial effects into account and thus ignoring spatial dependencies of poverty can cause inaccurate results and conclusions. All the measures of goodness of fit indicated an increase in fit from the OLS to the SEM model, with the best fit being achieved with the SLM model, implying that the use of this model resulted in more accurate estimates. The results for model selection for spatial differences (regression) indicate the following:

- The R - squared was higher in the SLM model than both OLS and SEM.
- The log - likelihood of the SLM model was the highest.
- The SLM model produced lower values of both AIC and SC (BIC).

In light of these results and in the hypothesis testing above, the following conclusion was generated: Spatial econometric models resulted in more accurate estimates than those achieved with the OLS model and the best fit of spatial econometric model to the data, based on the spatial weight matrix used, is the SLM.

The estimated SLM model is:

$\hat{y}_i = 0.642\hat{a}0.037(ED{-}NO){-}0.031(ED{-}PR){+}0.227(ED{-}HI)\hat{a}0.091(OCC{-}\ AGR) + 0.032(MS - MRD) - 0.209(Parity) - 0.045 * (USKL) + 0.396(Wy_i)$

Where Wy_i is the average Poverty rate in all neighbouring clusters, according to the spatial weight matrix use.

The final model (SLM) explains 79.20% of the variation in the rate of women poverty across Ghana. This final model includes only variables with statistically significant coefficients. The main variables associated with poverty among women in Ghana in 2008 were No education (ED - NO), Primary education (ED - PR), Higher education (ED - HI), unskilled manual works (OCC - USKL), a woman with Agriculture as the main source of livelihood (OCC - AGR), Parity, woman getting married (MS - MRD). While a woman's ability to obtain higher education and getting married decrease the likelihood of her falling into poverty. The other factors rather increase the likelihood of a woman falling into poverty.

It is worth noting that the explanatory variables such as average household size, female headed households, married without couple living together, clerical, service, were all insignificant in explaining the variation of the women's economic status.

Chapter 5

Summary of Findings, Conclusion and Recommendations

5.1 Introduction

In this chapter, the summary of findings, conclusions as well as the recommendations based on the findings of the study are presented.

5.2 Summary of Findings

This study used spatial econometric methods based on spatial autocorrelation techniques to explore the geographical distribution of women poverty in Ghana using 411 clusters obtained from 4,916 women respondents in 2008 GDHS data. The response variable is the median wealth factor scores per cluster and 13 explanatory variables obtained from 27 socioeconomic, demographic, and geographical variables using PCA.

The test for spatial dependence showed a positively significant spatially dependent (Moran's I = 0.396; p-value= 0.001) and indicates that neighboring clusters tend to have similar poverty rates (i.e. there is a persistence of women poverty in space). This value (0.396) indicates the extent to which the fortunes of a cluster are tight to that of neighboring clusters. That is 10% increase in poverty in a cluster will result in approximately 4% increase in poverty rates in the neighboring clusters and vice versa.

LISA maps further showed that the distribution of women poverty in Ghana is non-uniform and it is largely northern phenomenon. The map indicates positive spatially correlated of 17% Low-Low (poor clusters) and 30% High-High (nonpoor clusters). This implies that about 17% clusters have poverty rates above (we use wealth so an inverse relation) the average poverty rates and are neighbors of clusters with the same above average poverty rates and 30% clusters have poverty rate below average poverty rate and are neighbors of those whose poverty rates are below the average. The LL clusters are predominant in the northern part of the country and HH are also predominant in the southern part of the country. Hence the "hotspots "of poverty are concentrated in the three northern regions and the "coldspots "of poverty are located at southern part such as Kumasi and Accra. This clustering is consistent with World Banks (2011) mapping of poverty in Ghana where the headcount poverty and poverty gap were concentrated in the northern parts of the country.

From the Spatial regression analyses, SLM was found to fit the MWFS better than OLS and SEM, and the major significant determinants of women poverty in 2008 are the education related variables (no education, primary education, higher education), the number of children a woman is given birth to (Parity), some occupational related variables (Agricultural and unskilled manual) and marital status (married). The variables that have no significant relationships with poverty are female headed household, average household size, clerical, service, couple married without living together.

In education, the higher the level of educational attainment the less likelihood a woman will fall into poverty. Higher education has the greatest impact of decreasing the likelihood of a woman falling into poverty among the entire variable employed in the study and no education has the reverse effect. These results are not surprising but rather consistent with several studies. Anyanwu (2010) found that the level of educational attainment by the household head has a significant effect of reducing household poverty and the effects increases as the level increases. Achia et al. (2010) concluded that the higher level of educational attainment decrease the probability of a household being poor. Habyarimana (2015) established that higher education reduces poverty status of a household.

Agyeman et al. (2011) and Ennin et al. (2012) also conducted separate studies on poverty in Ghana using GSLLs and concluded that the educational level of household head was an important significant factor of determining poverty status of a household in Ghana. However, the results in this study are inconsistent with Spaho (2014) and Sekhampu (2013) whose studies found no significant relationship between household head level of education and poverty.

Marital status of the respondent also decreases the probability of a woman being poor. This is inconsistent with Sekhampu (2013) who established no significant relationship between marital status and poverty, even though the coefficient of marital status was having an effect of reducing poverty, as obtained in this study. For the occupational effect on women poverty, the results indicate that women whose primary sources of livelihood are agricultural based and unskilled manual works are likely going to fall into poverty. This result is in line with Agyeman et al. (2011) and Ennin et al. (2012) who had shown that households with agricultural based occupation were poorer than those with different primary occupations. The number of children a woman is given birth to have a significant effect of increasing the probability of her falling into poverty.

Surprisingly, contrary to wide believe that the gender of the household head significantly influences household poverty, more specifically that households headed by women were poorer than those headed by men, leading to the feminization of poverty (Anyanwu, 2010; Gbedemah et al. 2010; UN, 2010b; UN, 2010c). The study found no statistical evidence to support such claims, gender of household head did not significantly influence women poverty. The World Bank's

World Development Report, (2000) reports the lack of gender differences in poverty rates in most regions of the world, especially the Middle East. Spaho (2014) and Agyeman et al. (2011) also failed to established statistical evidence between poverty and female headed households.

Another amazing result is the lack of statistical evidence between household size and poverty, which is inconsistent with several studies (Sekhampu, 2013; Anyanwu, 2010; Habyarimana, 2015; Spaho, 2014; Agyeman et al., 2012; Ennin et al., 2011). This finding is rather consistent with Achia et al. (2010) who concluded that household size was insignificant when included in the multivariate
analysis.

5.3 Conclusion

The analysis of the study reveals the existence of positive spatial dependence in the woman's median factor scores and for several reasons, poverty in one community is affected by (or affects) poverty in neighboring communities. The northern parts of the country identified as the hotspots of women poverty whiles the southern part is the coldspots of women poverty. Moreover, our analysis suggests that regions as a causal factor per se is important and communities are indeed more likely to have high (low) women poverty rates depending on where they are located in the country.

This may be due to the reasons such as high birth rate, unskilled works, agricultural base occupation and low educational attainment which are heterogeneously distributed across Ghana and which are also identified, through spatial lag model, as the main determinants of women poverty in Ghana. For example we do see that parity tends to be concentrated in the northern parts of the country with high-high clusters of parity whiles southern part of the country are generally tend to have low-low clusters of parity.

5.4 Recommendations

Given the findings of this study, the following suggestions are recommended:

- Poverty is multi - dimensional and some of the factors that influence it might not be captured by the models used in this study. This is evidenced by the significance test of both simple LM and robust LM for both SEM and SLM. Further research could be carried out using more robust methods such as Spatial Durbin Model (SDM), Bayesian Spatial Statistical Methods and Matrix Exponential Spatial Structure (MESS) which were outside the scope of this study.

- The study used non - monetary poverty measurements, nevertheless, income as a component measure of poverty remained quite important as it allows one to gauge the extent to which individuals and households can access basic services. Further research need to be carried out by incorporating both income and expenditure of individual households.

- Government and Non - governmental organizations need to move towards more effective targeting of the poor women rather than embarking on generalized programs. In other words poverty alleviation policies should reflect the spatial nature of women poverty in the country

- Government and other stake holders working towards women empowerment should set up vocation training programmes for young school leavers, drop - outs and unemployed women in the hot spot women poverty areas.

- In addition, exiting vocational training centres should be upgraded to accommodate hundreds of women annually in non - fee paying training programmes such as fashion designing, hat/textile design, computer education, hairdressing/barbing etc.

- Similar to schemes existing for cocoa producers, various forms of incentive packages for producers of food crops could be created. These may include supply of essential items such as farm equipments, fertilizers, insecticites, pesticides and soap either free or at subsidized prices.

- Provide strong incentives (financial etc.) for trained teachers to locate to deprived schools in the northern and hotspot areas of women poverty.

- Provide scholarships to poor but brilliant female students from JHS to tertiary levels.

- Relevant institutions such as plan parenthood association of Ghana (PPAG) should be resource to enable it to embark of sensitization education on the need for family planning in the northern part of the country and other hotspots of poverty.

- Supporting the rationalization of pro-poor spending especially on women by increasing share of public expenditures going to well - targeted programs such as Livelihood Empowerment Against Poverty (LEAP) and Ghana
Health Insurance subsidies for the poor.

REFERENCES

[1] Achia, T.N.O (2014). Spatial Modelling and Mapping of Female Genital Mutilation in Kenya. BMC Public Health, 14:276

[2] Achia, T, Wangombe A and Khadioli, N (2010). A logistic regression model to identify key determinants of poverty using demographic andhealth survey data. European Journal of Social Sciences, 13(1): 38 - 45.

[3] Adebanji, A., Achia, T, Ngetich, R, Owuno, J and Wangombe, A (2008).

Spatial Durbin Model for Poverty Mapping and Analysis. European Journal of Social Sciences, Vol.5 No.4, 194-204

[4] Agyeman, A., Nuamah, N.N. and Oduro, F.T (2011). Comparative Analysis of Poverty Incidence and Patterns in the Forest and Savanna Zones of Ghana. Ghana J. Forestry, Vol. 27(2), 66-84.

[5] Anselin, L (2003). A Companion to Theoretical Economics. Blackwell Publishers Ltd, 311-331.

[6] Anselin, L., Bera, A.K., Florax, R.and Yoon, M.J (1996). Simple Diagnostic Test for Spatial Dependence. Regional Science and Urban Economics. 26, 77 104.

[7] Anselin, L (2005). Exploring Spatial Data With *GeoDa™*: A work Book. Center for Spatial Integrated Social Science and Spatial Analysis Laboratory, Department of Geography

[8] Anselin, L (2001). Rao's Score Test in Spatial Econometrics. Journal of Statistical Planning and Inference, vol. 97, pp.113 - 139.

[9] Anselin, L (1999). Spatial Econometrics. Bruton Center School of Social Science, University of Texas at Dallas, Richardson, TX 75083-0688.

[10] Anselin, L (2002). Under the hood: Issues in the Specification and Interpretation of Spatial Regression Models. Agricultural Economics, vol. 27, pp. 247 - 267.

[11] Anyanwu, J.C (2010). Poverty in Nigeria: A Gendered Analysis. Journal Statistique Africain, numero 11

[12] Atkinson, A.B (1987). On the Measurement of Poverty. Econometrica, Vol.55, No. 4, 749-764.

[13] Atkinson, A.B (2003). Multidimensional Deprivation: Contrasting Social

Wealth and Counting Approaches. Journal of Economic Inequality. Kluwer Publishers, Netherlands, Vol. 1, pp. 51-65.

[14] Babatunde, R.O, Omotesho, O.A, Olorunsanya, E.O and Owotoki, G.M (2008). Gender Difference in Resources Allocation among Rural Households in Nigeria: Implication for Food security and Living Standards. European Journal of Social Sciences, Vol. 4, 160-172

[15] Bekti, R.D, Rahayu, A and Sutikno (2013). Maximum Likelihood Estimation For Spatial Durbin Model. Journal of Mathematics and Statistics 9 (3): 169174

[16] Blackden, M.C. and Woden, Q (2006). Gender, Time Use, and Poverty in Sub-Saharan Africa. World Bank Working Paper No. 73.

[17] Bradshaw, S.and Linneker, B (2003). Challenging Women's Poverty. Catholic Institute for International Relations. London, UK.

[18] Chi, G,and Zhu, J (2008). Spatial Regression Models for Demographic Analysis. Popul Res Policy Rev. 27:17-42 DOI 10.007/s1113-007-9051-8.

[19] Crandall, M.S.and Weber, B.A (2004). Local Concentrations of Poverty, and Poverty Dynamics. American Journal of Agricultural Economics.

[20] Coudouel,A. , Hentschel,J.S and Woden, T (2009). Poverty measurement and Analysis.Economics,MPRA paper,10490

[21] Deepa, N, Chambers, R, Shah, K.M and Patesch, P (2000). Voices of the Poor: Crying Out for Change. Oxford University Press, New York, Washington .D.C.

[22] Duncan, B.A (2004). Women in Agriculture. Friedrich Ebert Foundation, 2nd Ed. Accra, Ghana.

[23] Ennin, C.C., Nyarko, P.K, Agyeman, A., Mettle, F. O, Nortey, E.N.N (2011).

Trend Analysis of Poverty in Ghana: Logit Approach. Research Journal of Mathematics 3(1): 20-27.

[24] FAO (2012). Gender Inequalities in Rural Employment in Ghana. Gender, Equity and Rural Employment Division.

[25] Fapohunda, T.M (2012). Women and Poverty Alleviation in Lagos, Nigeria. Britsh Journal of Humanities and Social Sciences. Vol. 3(2).

[26] Fry, K., Firestone, R.and Chakkraborty, N.M (2014). Measuring Equity with Nationally Representative Wealth Quintiles. Washington, DC: PSI

[27] Friedman, J and Schady, N (2009). How Many More Infants Are Likely to Die in Africa as a Result of the Global Financial Crisis? The World Bank Development Research Group, Policy Research Working Paper 5023.

[28] Fukuda-Parr, S (1999). What Does Feminization of Poverty Mean? It Isn't Just Lack of Income. Feminist Economist 5(2), 99-109.

[29] Getis, A., Ord, J.K (1992). The Analysis of Spatial Association by Use of Distance Statistics. Geographical Analysis, Ohio State University Press, Vol. 24, No. 3

[30] Gbedemah, C., Jones, N. and Perenznieto, P (2010). Gender Risk, Poverty and Vulnerability in Ghana: Is the LEAP Cash Transfer Programme Making a Difference? Overseas Development Institute Project Briefing, No.52.

[31] Geography, University of Illinois, Urbana-Champaign, Urbana, IL 61801, http://www.csiss.org/

[32] Goodchild, M.F (1986). Spatial Autocorrelation. Geo Books Publishers, Norwich, Canada.

[33] GSS, GHS (2009). Ghana Demographic and Health Survey 2008. Accra, Ghana.

[34] GSS (2013). Non - Monetary Poverty in Ghana. 2010 Population and Housing Census Report. Accra, Ghana.

[35] Habyarimana, F, Zewortir, T and Ramroop, S (2015). Analysis of Demographic and Health Survey to Measure of Poverty of Household in Rwanda. Africa Population Studies Vol. 29, No. 1.

[36] Higazi, S.F, Abdel - Hady, D.H and Al - Oulfi, S.A (2013). Application of Spatial Regression Models to Income Poverty Ratios in the Middle Delta Contiguous Counties in Egypt. Pat.sta.oper.res. Vol.IX No.1 pp93-110.

[37] Holt, J.B (2007). The Topography of Poverty in the United States: A Spatial Analysis Using County-Level Data. Prevention of Chronic Disease, vol. 4, no. 4.

[38] ILO (2005). Facts On Women at Work. Geneva.

[39] Jeffrey, D., Sachs, D., Andrews, D. and John, L (2001). The Geography of Poverty and Wealth. Scientific American. 71-74.

[40] Jolliffe, I.T. (2002). Principal component analysis, 2nd ed., Springer.

[41] Kalipeni, E.and Zulu, L.C (2010). HIV and AIDS in Africa: A Geographic Analysis at Multiple Spatial Scales. GeoJournal, Springer.

[42] Kriaa, M, Driss, S and Karray, Z (2011). Inequality and Spatial Disparities in Tunisia. Economic Research Forum, Working Paper Series No. 631.

[43] Kumi-Kyereme, K and Amo - Adjei (2013). Effects of Spatial Location and Household Wealth on Health Insurance Subscription among Women in Ghana. BMC Health Service Research, 13:221.

[44] LeSage, J (1999). The Theory and Practice of Spatial Econometrics. Department of Economics, University of Toledo. http://www.econ.utoledo.edu/

[45] LeSage, J. and Pace, R.K (2009). Introduction to Spatial Econometrics. Taylor & Francis Group LLC. London, New York.

[46] Lu, J., Zhang, L (2010). Evaluation of Parameters Estimation Methods for Fitting Spatial Regression Models. Forest Science 56(5). 505 - 515

[47] McFerson, H (2010). Poverty Among Women in Sub-Saharan Africa: A Review of Selected Issues. Journal of International Women's Studies. Vol. 11, No.4, 49-72.

[48] Minot, N and Baulch, B (2003). Poverty and Inequality in Vietnam: Spatial Patterns and Geographic Determinants. Inter-Ministerial Poverty Mapping Task Force. International Food Policy Research Institute (IFPRI) and Institute of Development Studies.

[49] Omideyi, A.K (2008). Poverty and Development in Nigeria: Trailing the MDGs ? Afr. J. Infect. Diseases. 1(1) : 3 - 13.

[50] Paradis, E (2013). Moran's Autocorrelation Coefficient In Comparative Methods, Springer, New York.

[51] PCI (2014). Women's Empowerment & Poverty: http://www.pciglobal.org/contact-pci/. Retrieved 2015-01-10 12:11:08.

[52] Peterman, A., Quisumbing, A., Behrman. and Nkonya, E (2010). Understanding Gender Differences in Agricultural Productivity in Uganda and Nigeria. International Food Research Institute, Discussion Paper 01003.

[53] Porter, G (2007). Transport, (Im)mobility and Spatial Poverty Traps: Issues for Rural Women and Girl Children in Sub-Saharan Africa. Overseas Development Institute, Chronic Poverty Research Centre. Stellenbosch, South Africa.

[54] Ranathunga, S and Gibson, J (2014). Determinants of Household Poverty in the rural Sector in Sri Lanka: 1990-2010. Economics 3(3): 43-49.

[55] Rupasingha, A and Goetz, S.J (2007). Social and Political Forces as Determinants of Poverty: A Spatial Analysis. The Journal of Socio-Economic, vol. 36. pp. 650 - 671.

[56] Sameti, M, Farahmand, S and Enayati, F (2013). A Spatial Analysis of Poverty in Arap and Muslim Countries. Faculty of Administrative Sciences and Economics, University of Isfahan, Iran.

[57] Saufie, A.Z, Yahya, A.S and Ramil, N.A (2011). Improving Multiple Linear Regression Model Using Principal Components Analysis for Predicting PM_{10} Concentration in Seberang Prai, Pulau Pinang. International Journal of Environmental Sciences, Vol.2 No.2, 415 - 422.

[58] SCGS (2002). Briefing Note for the Ghana Poverty Reduction Strategy. Country Gender Assessment, Ghana.

[59] Sekhampu, T.J. (2013). Determinants of Poverty in a South African Township, Journal of Social Sciences, 34(2): 145 - 153.

[60] Sekyere, A.B (2011). Ensuring Equitable Development in Ghana, Paper Presented at MDBS Annual Review Workshop, Accra.

[61] Sen, A.K, (1993). Capability and Well-Being. The Quality of Life. Pg. 30-53. Oxford Publications

[62] Sen, A.K (2014). Poverty and the Tolerance of the Intolerable. The Prospect /Joseph Rowntree Foundation Anti-poverty Lecture at the London School of Business.

http://www.prospectmagazine.co.uk/sound-and-vision/.org/amartya-sen-poverty/

[63] Sopipanet, N, Kanjanavajee, W and Sattayatham, P (2012). Forcasting SET50 Index with Multiple Regression Based on Principal Component Analysis. Journal of Applied Finance & Banking, Vol.2 No.3, 271-294.

[64] Sower, N. K (2002). An Assessment of Poverty Reducting Policies and Programmes in Ghana. Paper Presented at a MIMAP Workshop on Assessing Poverty Policies Held at Rabat, Morocco.

[65] Sowunmi, F.A, Akinyosoye, V.O, Okoruwa, V.O and Omonona, B. T (2012). The Landscape of Poverty in Nigeria: A Spatial Analysis Using Senatorial Districts-Level Data. American Journal of Economics, 2(5): 61 - 74.

[66] Spaho, A (2014). Determinants of Poverty in Albania. Journal of Educational and Social Research, Vol. 4 No.2

[67] Speer, A (2009). Spatial Relationships in Unemployment: City of Los Angeles. Economic Senior Project, Springer.

[68] Torres, O.M, Vost, S.A., Maneta, M.P, Wallender, W.W, Rodrigues, L.N, Bassoi, L.H. and Young, J.A (2011). Spatial Patterns of Rural Poverty: An Exploratory Analysis in the Sao Francisco River Basin, Brazil. Nova Economia Bello Horizonte, 21(1).

[69] UN (2010a). The World's Women 2010, Trend and Statistics. Department of Economic Affairs. Washington D.C.

[70] UN (2010b). The Millennium Development Goals Report. Washington D.C.

[71] UN (2012). Poverty Feminization Economic and Social Council. Washington D.C.

[72] UNDP (2012). 2010 Ghana Millennium Development Goals Report, Accra, Ghana.

[73] UNDP (2014). Sustaining Human Progress: Reducing Vulnerabilities and Building Resilience. Human Development Report 2014. Washington DC.

[74] Viton, P.A (2010). Notes on Spatial Econometric Models. City and Regional Planning 870.03

[75] Voss, P. R, Long, D.D, Roger, B.H and Friedman, S (2006). County Child Poverty Rates in the US: A Spatial Regression Approach. Popul Res Policy Rev, no. 25, pp. 369 - 391.

[76] Wrigley - Asante, C (2011). Women Becoming Bosses: Changing Roles in Decision Making in Dangme West District of Ghana. Journal of Geography, Vol.3. 60 - 87

[77] Yrigoyen, C.C, (2007). Spatial Econometric with Applications. Universidad Politecnicade Barcelona. 12-13, 18-20

[78] Zheng, Y and Zhu, J (2012). On the Asymptotics of Maximum Likelihood Estimation for Spatial Linear Models on a Lattice. Sankhyˉ*a*: The Indian Journal of Statistics. Vol. 74-A, Part 1, pp. 29-56.

REFERENCES

[1] Baidoo, A. (2013). The spread of hiv/aids in ghana. *International journal for the Spread HIV/AIDS*, 35:210–240.

[2] Barnett, W. A., He, Y., and Yansi, F. (2002). Stabilization policy as bifurcation selection: Would stabilization policy work if the economy really were unstable. ,. *Journal of Science Maths*, 5:1025–1052.

[3] Okyere, G. A. (2013a). *Introduction to LaTex*.

[4] Okyere, G. A. (2013b). Mathematics is for great thinkers. *Ghana Mathematical Journal*, 34:23.