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# MODELLING THE DYNAMIC RELATIONSHIP BETWEEN HYPERTENSION AND DIABETES CASES IN NORTHERN REGION

BY

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(UDS/MAS/0026/13)

THESIS SUBMITTED TO THE DEPARTMENT OF STATISTICS, FACULTY OF MATHEMATICAL SCIENCES, UNIVERSITY FOR DEVELOPMENT STUDIES IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF MASTER OF SCIENCE DEGREE IN APPLIED STATISTICS

OCTOBER, 2015

# **DECLARATION**

## Student

I hereby declare that this thesis is the result of my own original work and that no part of it has been presented for another degree in this university or elsewhere:

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## ABSTRACT

Hypertension and diabetes are among the well-known and potent risk factors for cardiovascular disease development globally and they rarely exist in isolation. This study therefore models the dynamic relationship between hypertension and diabetes cases in the Northern region of Ghana. Monthly data on hypertension and diabetes cases from the Tamale Teaching Hospital database was modeled using Vector Autoregressive model. Before fitting the model, the nature of the trend characterising the hypertension and diabetes cases were investigated. The results revealed that both hypertension and diabetes cases exhibit log-linear trend. Appropriate order of the Vector Autoregressive model was determined using the AIC, BIC, FPE and HQIC. The BIC selected lag 1 and HQIC selected lag 2. Both VAR (1) and VAR (2) models were fitted to the data and the LRT used to select the best. The results from the LRT revealed that the VAR (2) model was best for modeling the dynamic relationship between the hypertension and diabetes cases. The diagnostic checks of the VAR(2) model using both the univariate and multivariate Ljung-Box test and the ARCH-LM test revealed that the model was free from serial correlation and conditional heteroscedasticity respectively. The JB test revealed that the normality assumption of the VAR (2) model was satisfied. An infernce with the model using the Grange causality test revealed that there was a unidirectional relationship between hypertension and diabetes whiles the instantaneous causality test revealed that there was a bilateral relationship between the cases. The FEVD revealed that both hypertension and diabetes cases explain some amount of forecast uncertainty in each other.

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# **DEDICATION**

This work is dedicated to my dear mother, Hajia Adamu Benson whose effort has brought me this far.

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# LIST OF ACRONYMS

ACF	Autocorrelation Function	
ADF	Augmented Dickey-Fuller	
ADF	Augmented Dickey-Fuller	
AIC	Akaike Information Criterion	
AICc	Akaike Information Criterion corrected	
AR	Autoregressive	
ARCH-LM	Autoregressive Conditional Heteroscedast	icity Lagrange Multiplier
ARIMA	Autoregressive Integrated Moving Average	e
ARIMAX	Autoregressive Integrated Moving Average	e model with covariates
BIC	Bayesian Information Criterion	
CUSUM	Cumulative Sum	
CV	Coefficient of Variation	
CVD	Cardiovascular Diseases	
df	Degrees of freedom	
DF	Dickey-Fuller	
FEVD	Forecast Error Variance Decomposition	
LCL	Lower Confidence Limit	

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LRT	Likelihood Ratio Test	
MA	Moving Average	
MAE	Mean Absolute Error	
MAPE	Mean Absolute Percent Error	
Max	Maximum	
Min	Minimum	
MPE	Mean Percent Error	
PACF	Partial Autocorrelation Function	
RMSE	Root Mean Square Error	
SARIMA	Seasonal Autoregressive Integrated Mo	oving Average
TTH	Tamale Teaching Hospital	
UCL	Upper Confidence Limit	
VAR	Vector Autoregressive Model	
WHO	World Health Organisation	
МоН	Ministry of Health	
VEC	Vector Error Correction	

JB Jarque-Bera test

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# **CHAPTER ONE**

#### **INTRODUCTION**

#### 1.1 Background of the Study

Cardiovascular diseases (CVDs) are among the leading causes of mortality and morbidity that are usurping the minds of public health workers and other stakeholders in the health sector globally. They are group of disorders of the heart and blood vessels that have been estimated to cause 17.5 million deaths in the year 2012, representing 31% of all global deaths. Over three quarters of CVD deaths take place in low- and middle-income countries (WHO, 2015).

Hypertension and diabetes are among the major risks factors contributing to CVDs globally and they rarely exist in isolation. Myriad of researchers have reported that there exist a significant relationship between hypertension and diabetes. For instance, Landsberg and Molitch (2004) reported that in the United State (US) population, hypertension occurs in approximately 30% of patients with type 1 diabetes and in 50% to 80% with type 2 diabetes. Also, a prospective cohort study in the US reported type 2 diabetes mellitus was almost 2.5 times as likely to develop in subjects with hypertension as in subjects with normal blood pressure (Gress *et al.*, 2000). Again, White (2007) reported that hypertension in patients with diabetes is common, but there are important differences between hypertension in type 1 and type 2 diabetes.



patients with type 1 diabetes often have hypertension secondary to nephropathy.

Hypertension and diabetes have emerged as major medical and public health issues world-wide. According to the World Health Organisation (WHO), the prevalence of diabetes in adults worldwide was estimated to be 4.0% in 1995 and it is predicted to rise to 5.4% by the year 2025 such that the number of adults with diabetes in the world would rise from 135 million in 1995 to 300 million in the year 2025 (King *et al.*, 1998). Additionally, one billion people worldwide are suffering from hypertension (Chobanian *et al.*, 2003) and it is expected that by 2025, up to 1.56 billion adults worldwide will be hypertensive (Kearney *et al.*, 2005). The high prevalence of the CVD risk factors makes them significant factors for mortality and morbidity.

In Ghana, Burket (2006) conducted a blood pressure survey in two communities in the Volta region and found that the prevalence of hypertension in the population considered was 38.2%. He also revealed that more than 80% of those with hypertension history had elevated blood pressure at the time of screening. Danquah *et al.* (2012) also researched into the characteristics and associated factors of type 2 diabetes in Kumasi and found that 97% of the patients were on medications and 63% of them were hypertensive as well. Diabetic complications occurred in 20% of the patients. Also, Bennin and Essuman (2014) evaluated the effectiveness of blood pressure treatment in mild to moderate hypertension at the Korle-Bu polyclinic, Accra. They evaluated charts of patients managed at the polyclinic

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from the year 2005 to 2007. Their study revealed that about 26.7% of patients diagnosed and on drug had a decreased in blood pressure of 20 mmHg (systolic) and about 27.7% of the patients with age less than 40 years had elevated blood pressure.

These two risk factors (hypertension and diabetes) of CVDs that do not operate in isolation affect the same major target organs. The most common denominator of hypertensive/ diabetic target organ-disease is the vascular tree. People with coexisting hypertension and diabetes are at increased risk of developing atherosclerosis, retinopathy, renal failure and non traumatic amputation (Stamler, 1993). Knowing the deadly risk of these two factors, it is imperative to investigate their pattern and the dynamic relationship between them. This would help public health workers, government and other stakeholders in the health sector to organize educative programs for citizens on causes of hypertension/ diabetes and their associated effects in order to reduce the menace.

This study therefore investigates the dynamic relationship between hypertension and diabetes cases in Northern Region using Vector Autoregressive (VAR) model.

#### **1.2 Problem Statement**

Hypertension and diabetes are among the most well-known and potent risk factors for CVDs development globally. Hypertension is usually found in approximately 40% to 60% of patients with type 2 diabetes (Sowers *et al.*, 2001; Arauz-Pacheco *et al.*, 2002). These risk factors creates a huge economic



burden not only due to direct cost of treatment particularly of their complications, but also in terms of man hours lost due to the debilitating effect these diseases have on the individual and his or her family and society as a whole.

Epidemiological studies have shown that diabetes is increasing rapidly in people of South Asia, African and African Carribean origins (Oldroyd et al., 2005). In addition, there exist an approximately 89% increase of hypertension in Sub-Saharan Africa from 2000 through 2025 versus a 24% increase in more developed countries. Among the WHO regions, the prevalence of hypertension was highest in Africa, where it was 46% for both sexes combined (Global Health Observatory, 2012). In Ghana, the prevalence of hypertension in Urban Accra was estimated to be 28.3% (crude) and 27.3% (age standardised) (Amoah, 2003). Also, a study on the changing patterns of hypertension in four rural communities in Ghana showed prevalence of 25.4%. The study also revealed that of those with hypertension only 32.3% had prior knowledge of their conditions and less than half of these were on treatment (Addo et al., 2006). Cappucio et al. (2004) in their study in the Ashanti region divulged a prevalence of hypertension of 28% for the Ashanti tribe in Ghana. According to Amoah et al. (2002), the prevalence of diabetes in the Greater Accra region was 6.3% and type 2 diabetes constitutes 90% of the reported cases.

A number of studies have revealed that there exist a relationship between hypertension and diabetes. Studies in Africa have reported high prevalence of

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hypertension in diabetes patients, although most are clinic based. A study conducted in Kenya by Otieno *et al.* (2005) to determine the proportion of specific cardiovascular risk factors in ambulatory patients with type 2 diabetes revealed that 50% of the patients had hypertension. In a Nigerian clinic population, hypertension and diabetes coexisted in 9.7% of the patients studied (Ogunleye *et al.*, 2012).

The increasing trend of these risk factors could be very detrimental to the economic development of any country and the world as a whole. Governments and other health organizations need to invest billions of dollars into the health sector in order to curb this problem. Therefore knowing the pattern of these diseases and how they related at an early stage could aid world health bodies to plan and develop policies that would be used to curb the growing trend of these harmful diseases. Hence this study investigates the pattern and models the relationships between hypertension and diabetes in the Northern region of Ghana.

#### **1.3 General Objective**

The main objective of this study is to develop multivariate time series model for describing the dynamic relationship between diabetes and hypertension in Northern Region.

## **1.3.1 Specific Objectives**

i. To investigate the nature of trend characterizing both diabetes and hypertension cases in Northern Region.



- ii. To fit Vector Autoregressive (VAR) model for describing the short run relationship between hypertension and diabetes cases.
- iii. To investigate how hypertension and diabetes cases react to each other with time due to a sudden change in one another.
- iv. To determine the magnitude of forecast uncertainty in one endogenous variable (hypertension/diabetes) that is explained by the other endogenous variable considered over time, therefore assessing whether the knowledge of the behavior of one endogenous variable improves the forecast of another endogenous variable.

#### 1.4 Significance of the Study

The findings of this study could be used by the Ministry of Health (MoH) to develop policies to reduce the pattern of these diseases in the Northern region. In addition, the findings of the study could give insight about the pattern of these diseases in Ghana, therefore providing basis for further research about these diseases in Ghana as a whole. Finally the findings of this study would contribute significantly to existing literature in health studies.

#### 1.5 Structure of the Thesis

The thesis is organized into five chapters. Chapter one contains the introduction of the research work. Chapter two comprises of literature review. Chapter three outlines the methodology employed in this research while chapter four presents the analysis and discussion of results. Chapter five is devoted to conclusion and recommendations.

## **CHAPTER TWO**

## LITERATURE REVIEW

#### **2.0 Introduction**

This chapter reviews empirical works done on hypertension, diabetes and some relevant time series methods that has been used in medical researches.

#### 2.1 Empirical researches on Hypertension and Diabetes

A number of researches have been carried out on hypertension and diabetes using different methodologies. Below are some of them;

Burket (2006) conducted a blood pressure survey in two communities in the Volta region and found that the prevalence of hypertension in the population considered was 38.2%. He also revealed that more than 80% of those with hypertension history had elevated blood pressure at the time of screening.

Danquah et al. (2012) also researched into the characteristics and associated factors of type 2 diabetes in Kumasi and found that 97% of the patients were on medications and 63% of them were hypertensive as well. Diabetic complications occurred in 20% of the patients. Also, Bennin and Essuman (2014) evaluated the effectiveness of blood pressure treatment in mild to moderate hypertension at the Korle-Bu polyclinic, Accra. They evaluated charts of patients managed at the polyclinic from the year 2005 to 2007. Their study revealed that about 26.7% of patients diagnosed and on drug had a decreased in blood pressure of 20 mmHg



(systolic) and about 27.7% of the patients with age less than 40 years had elevated blood pressure.

Also, a study on the changing patterns of hypertension in four rural communities in Ghana showed prevalence of 25.4%. The study also revealed that of those with hypertension only 32.3% had prior knowledge of their conditions and less than half of these were on treatment (Addo *et al.*, 2006).

Cappucio *et al.* (2004) in their study in the Ashanti region divulged a prevalence of hypertension of 28% for the Ashanti tribe in Ghana. According to Amoah *et al.* (2002), the prevalence of diabetes in the Greater Accra region was 6.3% and type 2 diabetes constitutes 90% of the reported cases.

Keita *et al.* (2005) conducted a study to look at the cost-effectiveness analysis of hypertension treatment using controlled release Nifedipine and candesartan low-dose combination therapy in patients with essential hypertension in Japan, they concluded that low-dose combination therapy of controlled release nifedipine and candesartan was "dominant" to up-titrated monotherapy with candesartan in essential hypertensive patients and therefore recommended a combination treatment strategy because that could decrease the financial burden on the National Health Insurance System in Japan.

Next, Tatsuya *et al.* (2007) conducted a study to compare the effects of telmisartan and olmesartan on home blood pressure, glucose and lipid profiles in patients with hypertension, chronic heart failure and metabolic syndrome and found that one-daily telmisartan at a dose of 40mg reduce morning hypertension



and improve lipid and glucose metabolism as compared to once-daily 20mg olmesartan. This means telmisartan may be more beneficial than olmesartan in the management of hypertension, chronic heart failure and metabolic syndrome.

Also, Deepa *et al.* (2003) conducted a research in south India to assess whether the rule of halves in hypertension was still valid. They found that the overall prevalence of hypertension in the population considered was 22.1% (279/1262) prevalence was higher in subjects with glucose intolerance. The awareness and treatment of hypertension was slightly higher among the diabetic hypertensive subjects. They concluded that the rule of halves is still valid in the urban south Indian population and thus the awareness, treatment and control measures for hypertension are still inadequate in population.

Also, Kartharina *et al.* (2003) conducted a research on hypertension prevalence and blood pressure level in six European countries, United States and Canada. They reported the adjusted prevalence of hypertension was 28% in the North America countries at 140/90mmHg. The findings for men and women were similar. Hypertension prevalence was strongly correlated with stroke mortality (r=0.78). They also found that hypertension was 60% higher in Europe as compared to the United States and Canada.

Another contribution to the study of hypertension was made by Erhun *et al.* (2005). They conducted a research to determine the prevalence of hypertension in a University Community in South West Nigeria. They found out that the overall crude prevalence was 21% of the population considered. About 16% of these

were already on treatment and about 32% of the subjects had more than 3 children. The study also showed that subjects with eye problem, diabetic and took local kola nuts were 18.6%, 1.9% and 7.4% respectively. The study also established no significant relationship between coffee consumption and hypertension. They recommended that awareness of the disease and other cardiovascular risk factors be increased and the populace be encouraged to have self-measurement blood pressure devices.

Zuleat (2007) conducted a research to look at the incidence of hypertension among a selected adult population in the Niger Delta region of Nigeria. She considered two hundred people for the study, the male group was commercial motorcyclists and the female groups were market women. The study showed that the incidence of hypertension among motorcyclists was 16% whiles that of the market women was 12%. She therefore concluded that there is the need for more studies in the Niger Delta region using a larger sample size and different category of people.

Patricia *et al.* (2004) conducted a study to examine the prevalence and the level of awareness, treatment and control of hypertension in different world regions. They reported that the prevalence of hypertension varied around the world, with the lowest prevalence in rural India (3.4% in men and 6.8% in women) and the highest prevalence in Poland (68.9% in men and 72.5% in women). Awareness of hypertension was reported for 46% of the studies and varied from 25.2% in Korea to 75% in Barbados and treatment varied from 10.7% in Mexico to 66% in



Barbados. Control (blood pressure < 140/90 mmHg while on antihypertensive medication) varied from 5.4% in Korea to 58% in Barbados.

Amos *et al.* (2013) conducted a study to determine the prevalence and risk factors for hypertension in Adansi south, Ghana. They revealed that one third (27.19%) of the sample (N=539) considered was hypertensive. The report also showed that the highest percentage of hypertension respondent were in 40 to 59 age group (39%). There was a twofold increase in the percentage of the respondent with hypertension between 13 to 19 and 30-39 age group and therefore calls for health education and promotion intervention among adolescent and young adults in Adansi south.

Amoah (2003) conducted a research to determine the prevalence of hypertension and the extent to which it is controlled among adult Ghanaians. The research showed a crude prevalence of 28.3%. The age-standardized prevalence, to the new standard world population, was 28.4%, the mean systolic and diastolic blood pressures increased with age. About 1337 subjects had hypertension of which 34% were aware of the condition, 18% were treated and 4% had their blood pressures less than 140/90 mm Hg. He therefore concluded that hypertension is a major health issue which is associated with relatively low level of awareness, drug treatment and blood pressure control. Prevention strategies such as reduction in salt intake and integration of hypertension care into primary care may be beneficial.

Kearney *et al.* (2005) studied the global burden of hypertension worldwide, the study covered published literature from 1980, to 2002, using Medical Literature Analysis and Retrieval System Online (MEDLINE), supplemented by a manual search of bibliographies of retrieved articles. The study showed that on overall,  $26\cdot4\%$  of the adult population in 2000 had hypertension ( $26\cdot6\%$  of men and  $26\cdot1\%$  of women and 29.2% were projected to have this condition by 2025 ( $29\cdot0\%$  of men and  $29\cdot5\%$  of women. The estimated total number of adults with hypertension in 2000 was 972 million , 333 million in economically developed countries and 639million in 2025 was predicted to increase by about 60% to a total of 1.56 billion.

Athanasakis *et al.* (2014) modeled a short-term cost-effectiveness analysis of hypertension treatment in Greece. Health-resource use data and clinical outcomes for a cohort of 1453 hypertensive patients in Greece who were prospectively followed for a 1-year period served as the primary data for the analysis. Based on these data, the incremental cost per mmHg lowering in the baseline blood pressure (BP) and the incremental cost per patient that achieved BP control after 1 year of treatment were estimated. Costs were calculated from a social security perspective and are reported in year 2011 values. The average cost per mmHg lowering of baseline BP for the whole study sample was  $\epsilon_{13.7 \pm 14.2}$ , ranging from  $\epsilon_{20.3 \pm 21.4}$  for Grade 1 hypertension patients to  $\epsilon_{9.9 \pm 4.4}$  for Grade 3. The average cost per patient that achieved control after 1 year of treatment was  $\epsilon_{603.1 \pm 215}$ , with a range from  $\epsilon_{496.1 \pm 186.6}$  to  $\epsilon_{868 \pm 258.2}$  for Grades 1 and

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3 baseline BP, respectively. The sensitivity analysis corroborated the results. The present study outcomes compare favorably to corresponding results from the international literature and indicate the clinico-economic value of hypertension treatment in Greece, especially to those that were severely ill. In the light of the current financial situation, resource allocation based on evidence from economic evaluation constitute a core input in the decision-making process for health policy.

Abdulsalam et al. (2014) determined the prevalence and the association of modifiable risk factors with hypertension in a rural community in Oyo State South Western Nigeria. A cross sectional study was conducted among 166 male and 201 female adults of 18 years and above using cluster sampling technique. Hypertensive subjects were defined as those with systolic greater than or equal to 140 and diastolic of 90mmHg. The mean age of the subjects was  $36.36 (\pm 16.88)$ years and mean systolic and diastolic pressures were  $124 (\pm 16.93)$  and 76.32 $(\pm 11.85)$  mmHg, respectively. The prevalence of hypertension was high (22.9%)in rural communities but awareness was low (10.71%). The prevalence of alcohol consumption, sedentary lifestyle, abnormal weight, inadequate sleep, smoking, significant stress, and female use of hormonal contraceptives was 149 (40.6%), 91 (24.8%), 88 (24.0%), 122 (33.2%), 14 (3.8%), 65 (17.7%), and 53 (26.5%), respectively. Overweight, sex, inadequate sleep, and stress were established as positive predictors of hypertension. The rising prevalence of hypertension and its modifiable risk factors in rural communities require prompt interventions directed at reversing these trends.

Wild *et al.* (2004) conducted a study to estimate the prevalence of diabetes and the number of people of all ages with diabetes from year 2000 to 2030 worldwide. They considered urban and rural populations separately for developing countries. The prevalence of diabetes was estimated to be 2.8 % in 2000 and 4.4 % in 2030. That is, the total number of people with diabetes was projected to rise from 171 million in 2000 to 366 million by 2030. The study also showed that most important demographic prevalence worldwide appears to increase in the proportion of people above 65 years of age. They concluded that the "diabetes epidemic" will exist even if the level of obesity remains constant. Given the increasing prevalence of obesity, it is likely that the figures provided will be an underestimate of future diabetes prevalence.

King *et al.* (1998) also conducted a research on the prevalence of diabetes in adults worldwide. They reported that the estimated prevalence was 4.0% in 1995 and may rise to 5.4% by the year 2025. The study also showed that the prevalence is higher in developed than in developing countries and that the number of adults with diabetes worldwide will rise from 135 million to 300 million by the year 2025.

Bin- Lu *et al.* (2010) conducted a research to determine the prevalence of Diabetic Peripheral Neuropathy (DPN) and risk factors associated with DPN in type 2 diabetic patients in the Shanghai downtown. About 435 diabetic patients were selected for the study. These subjects were evaluated on complete foot examination, body mass measurement, resting blood pressure, fasting blood measure, urinary Albumin-to-Creatinine Ratio (ACR). The study showed that the prevalence of DPN was 61.8% among Chinese patients diagnosed with type 2 diabetes in the Shanghai downtown.

Again Aekplakorn *et al.* (2011) found that higher prevalence of diabetes was found in women, older individuals, and urban areas; however, undiagnosed diabetes as proportion of all diabetes was higher in men and in those with less than a secondary education. They compared their finding to the 2004 study in which the prevalence of diabetes in 2004 increased slightly in the 2009 research and diabetic subject were more likely to be obese and have high cholesterol. The proportion of individuals with diabetes that was diagnosed, treated and controlled for blood glucose, blood pressure and serum cholesterol improved in 2009. However, the proportion remained substantially low.

Maguy *et al.* (2012) conducted a research on diabetes and coronary heart disease. The study showed that diabetes mellitus is associated with an increase in cardiovascular deaths and a higher incidence of cardiovascular diseases including coronary heart disease. The study also showed a rise in prevalence of diabetes which will lead to an increase in the demand for primary, secondary and tertiary health services globally.

Harris *et al.* (1998) also investigated the prevalence of diabetes, impaired fasting glucose and impaired glucose tolerance in U.S. adults. The study revealed that the prevalence of diagnosed diabetes in 1988 to 1994 was estimated to be 5.1% for U.S. adults 20 years and above. According to the American Diabetes Association criteria the prevalence of undiagnosed diabetes was 2.7% (5.4 million) and the



prevalence of impaired glucose was 6.9% and the rates of diabetes were similar. Based on the American Diabetes Association criteria, the prevalence of diabetes (diagnosed plus undiagnosed) in people who were 40 to 70 years of age increased from 8.9% from 1976 to 1980 and 12.3% from 1988 to 1994.

Catherine *et al.* (2006) also conducted a research to determine the prevalence of diabetes and fasting glucose in adults in U.S. population. The study revealed that the crude prevalence of total diabetes in 1999 to 2002 was 9.3% (19.3 million, 2002 U.S population), consisting of 6.5% diagnosed and 2.8% undiagnosed. About 26.0% had impaired fasting glucose representing 35.3% (73.3 million) with either diabetes or impaired fasting glucose. The prevalence for total diabetes for subjects aged 65 years and above was 21.6%. The study also showed that the prevalence of diagnosed diabetes was similar by sex but prevalence of undiagnosed diabetes and impaired fasting glucose was significantly higher in men. There was an increase in the crude prevalence from 5.1% in 1988 to1994 to 6.5% in 1999 to 2002 but the crude was stable for undiagnosed diabetes.

McLarty *et al.* (1989) also looked at the prevalence of diabetes and impaired glucose tolerance in rural Tanzania using the World Health Organisation criteria. The study revealed that 0.87% of the subjects selected for the study had diabetes and 7.8% had impaired glucose tolerance. The prevalence rates were 1.1% and 8.4% respectively. They concluded that diabetes and impaired glucose tolerance did not differ significantly between villages despite socioeconomic, geographical and dietary differences.

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Furthermore, Amoah *et al.* (2002) also determine the prevalence of diabetes in Greater Accra, Ghana. Their study revealed that the prevalence of diabetes was 6.3%. Out of the 300 subjects with diabetes, 209 (69.7%) had no prior history of the disease. The age group 64 years and above had the highest prevalence of 13.6% of diabetes. The adjusted age prevalence of diabetes, impaired fasting glycaemia and impaired glucose intolerance were 6.4%, 6.0% and 10.7% respectively. The study also showed that diabetes are more common in men (7.7%) than in women (5.5%).

Yancy *et al.* (2005) researched into a low-carbohydrate, ketogenic diet (LCKD) to treat type-2 diabetes. The study recruited 28 overweight participants with type 2 diabetes for a 16-week single-arm pilot diet intervention trial. Twenty-one of the 28 participants who were enrolled completed the study. Twenty participants were men; 13 were White, 8 were African-American. The mean [ $\pm$  SD] age was 56.0  $\pm$ 7.9 years and BMI was 42.2  $\pm$  5.8 kg/m<sup>2</sup>. Hemoglobin decreased by 16% from 7.5  $\pm$  1.4% to 6.3  $\pm$  1.0% (p < 0.001) from baseline to week 16. Diabetes medications were discontinued in 7 participants, reduced in 10 participants, and unchanged in 4 participants. The mean body weight decreased by 6.6% from 131.4  $\pm$  18.3 kg to 122.7  $\pm$  18.9 kg (p < 0.001). The LCKD improved glycemic control in patients with type 2 diabetes such that diabetes medications were discontinued or reduced in most participants. Because the LCKD can be very effective at lowering blood glucose, patients on diabetes medication who use this diet should be under close medical supervision or capable of adjusting their medication.



EI Elamin *et al.* (2015) evaluated the effects of fasting in healthy Muslims from three different nationalities in Dubai. The parameters studied included the body mass index, fasting lipid profile, blood glucose and HBA1c in 49 healthy Muslim volunteers. These individuals belong to three different ethnicities; Pakistanis, Sudanese and Emiratis. The study showed a significant difference in body weight and BMI in all subjects of three nationalities. Total cholesterol increased significantly in the Pakistani group compared to the other population at the end of Ramadan. There was a statistically significant increase in the HDL among females.

Olatunbosun *et al.* (1998) also studied the prevalence of diabetes mellitus and impaired glucose tolerance in adults in Ibadan, Nigeria. A total of 998 subjects was randomly selected from five ministries and department of the government sector was considered for the study. Their study revealed that seven subject were diabetic representing a prevalence of 0.8% and nineteen subjects were impaired glucose tolerance representing a prevalence of 2.2%. There was no sex difference between the two groups.

Nwafor and Owhoji (2001) also determined the prevalence of diabetes among Nigerians in Port Harcourt. The study population was randomly selected and classified in to two socio-economic statuses as high or low. The prevalence of diabetes was 23.4% among the high socio-economic group and 16% among the low socio-economic group. Undiagnosed diabetes occurred in 18.9% of the population studied. Sutapa (2014) modelled frequency of food consumption and self-reported diabetes among adult men and women in india: A Large Scale Nationally Representative Cross-sectional Study. Cross sectional data of 99,574 women and 61,361 men aged 20-49 years who participated in India's third National Family Health Survey conducted during 2005-06 was used for this study.

Trojak (2014) studied the nonalcoholic fatty liver disease in patients with type 2 diabetes (NAFLD). The disease is recognized in 20 to 30% of general population but among the people with impaired glucose metabolism this fracture is about 70 to 90%. The study agreed with the numerous researches proving significant differentiation of various risk factors of diseases among men and women. The study examined 184 patients, 77 women and 107 men. Based on statistical analysis it was found out that sex is significant determinant of NAFLD.

Ghorbani (2013) researched into best herbs for managing diabetes. Most studies recommendations are based on animal studies and limited pieces of evidence about their clinical usefulness. However, his review focused on the herbs, the hypoglycemic actions of which have been supported by three or more clinical studies. The search was done in Google Scholar, Medline and Science Direct databases using the key terms diabetes, plants, herbs, glucose and patients. According to the clinical studies, *Aegle marmelos, Allium cepa, Gymnema sylvestre, Momordica charantia, Ocimum sanctum, Nigella sativa, Ocimum sanctum, Panax quinquefolius, Salacia reticulate, Silybum marianum and Trigonella foenum-graecum* have shown hypoglycemic and, in some cases, hypolipidemic activities in diabetic patients. Among them, *Gymnema sylvestre*,

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Momordica charantia, Silybum marianum and Trigonella foenum-graecum have acquired enough reputation for managing diabetes. The study concluded that physicians can rely on these herbs to advise patients their health.

# 2.2 Empirical Researches on the Relationship between Hypertension and Diabetes

Omar *et al.* (1988) conducted a community survey to assess the prevalence of diabetes and hypertension in Indians living in Durban. The study revealed that 9% of the subjects considered for the study had diabetes and 14.2% had hypertension. Diabetes mellitus was common in women (10.5%) than men (7%), whereas the prevalence of hypertension was similar in both sexes, that is women 13.5% and 14.7% in men. Hypertension was found in 45.8% of the diabetic subjects, 31.4% of subjects with impaired glucose tolerance and 9.9% of those with normal glucose tolerance. Although hypertension was common in women (37.9%) in the diabetic group, there was no significant difference in the sex distribution of subjects with impaired glucose tolerance and those with normal glucose tolerance.

Epstein (1997) also studied into the relationship between diabetes and hypertension and they found out that diabetes mellitus and hypertension are interrelated diseases that strongly predispose people to atherosclerotic cardiovascular diseases. Hypertension is about twice as frequent in individuals with diabetes as in those without. The prevalence of coexisting hypertension and diabetes appears to be increasing in industrialized nations because populations are aging, and both hypertension and non-insulin-dependent diabetes mellitus

increase with age. They estimated that 35 to 75% of diabetic cardiovascular and renal complications can be attributed to hypertension. The study also revealed that essential hypertension accounts for majority of hypertension in individual with diabetes, particularly those with non-insulin-dependent diabetes mellitus, who constitute over 90% of those with a dual diagnosis of diabetes and hypertension. Diabetic nephropathy also occurs after 15 years of diabetes in one-third of those with insulin-dependent diabetes and 20% of those with non-insulin-dependent diabetes mellitus which is an important contributing factor to the development of hypertension in the diabetic

Tai *et al.* (1991) also conducted a study to assess the link between hypertension and diabetes in Taiwan. A total of 11478 subjects were considered for the study and their blood glucose and blood pressure levels measured. The age-and-sexadjusted prevalence of hypertension among diabetes subjects were twice that of non-diabetes subjects. Hypertensive subjects had a higher prevalence of diabetes than normotensive subjects. Among hypertensive subjects the prevalence of diabetes was 12.7% for those taking antihypertensive drugs and 9.1% for those taking any drug.

Next, Ozlem and Nimet (2010) also researched into the relationship between hypertension, diabetes and obesity in Gaziantep, a city in Turkey. One thousand six hundred and one diabetes mellitus, hypertension and obesity patients were considered for the study .About 18.1% of the patients had hypertension, diabetes and obesity, 16.1% had hypertension and diabetes mellitus. About 16.1% had



only hypertension; 15.4% had obesity and hypertension; 13.3% had diabetes; 12.7% had obesity and 8.4% had obesity.

Benard *et al.* (2008) conducted a study to determine the relationship between hypertension and dysglycemia in Hong Kong. The study revealed that 58% of diabetes patients were also hypertensive and 56% of hypertensive patients were also diabetic. It was also found that hypertension and diabetes were both related to age and obesity indexes.

Landsberg and Molitch (2004) reported that hypertension occurs in approximately 30% of patients with type 1 diabetes and from 50 to 80% of patients with type 2 diabetes in United State (US) population.

Campbell *et al.* (2011) reviewed hypertension in people with type 2 diabetes. The reviewed showed that, pathogenesis of hypertension in patients with diabetes is complex, involving a range of biological and environmental factors and genetic predisposition; as a result, hypertension in people with diabetes incurs higher associated risks and adverse events. Mortality and morbidity are heightened in diabetes patients who do not achieve BP control (ie, a target value of less than 130/80 mm Hg). Often, combinations of 2 or more drugs (diuretics, angiotensin-converting enzyme inhibitors,  $\beta$ -blockers, angiotensin receptor blockers, calcium channel blockers, spironolactone, etc) are required for pharmacotherapy to be effective, particularly for patients in whom BP is difficult to control. However, the health care costs associated with extensively lowering BP are substantially less than the costs associated with treating the complications that can be prevented


by lowering BP. Detecting and managing hypertension in people with diabetes is one of the most effective measures to prevent adverse events, and pharmacotherapy is one of the most effective ways to maintain target BP levels in primary care.

Poljičanin et al. (2010) assessed the health-related quality of life (HRQoL) among people with diabetes or hypertension. They estimated the effect of cardiovascular comorbidities on HRQoL as well as compare HRQoL in these groups with that of healthy individuals. A total of 9,070 respondents aged 18 years and over were assessed for HRQoL. Data were obtained from the Croatian Adult Health Survey. Respondents were divided into five groups according to their medical history: participants with hypertension (RR), hypertension and cardiovascular comorbidities (RR+), diabetes mellitus (DM), diabetes and cardiovascular comorbidities (DM+) and participants free of these conditions (healthy individuals, HI). HRQoL was assessed on 8 dimensions of the SF-36 questionnaire. Participants with diabetes and those with hypertension reported comparably limited (p > 0.05) HRQoL in all dimensions of SF-36, compared with healthy individuals (p < 0.05). If cardiovascular comorbidities were present, both participants with diabetes and participants with hypertension had lower results on all SF-36 scales (p > 0.05) than participants without such comorbidities (p < 0.05). The results remained after adjustment for sociodemographic variables (age, sex, employment, financial status and education). Their research concluded that diabetes and hypertension seem to comparably impair HRQoL. Cardiovascular comorbidities further reduce HRQoL in participants with both chronic conditions.

Zivyat et al. (2014) studied the epidemiology of hypertension (HT) and its relationship with type 2 diabetes and obesity in eastern Morocco. They sampled 1628 adults aged 40 years and older, recruited voluntarily by using the convenience sampling method through 26 screening campaigns in urban and rural areas of the east of Morocco. 516 hypertensive people were enumerated (31.7%), without significant difference between women (32.5%) and men (30.2%). The known hypertensive people represent 10.1% of the whole sample. The frequency of HT, increases with age and it is more marked in rural (39.9%) than in urban areas (29%) (p < 0.001). It is significantly very high in diabetic subjects (69.9%) than among the non-diabetic ones (27.4%) (p< 0.001). The odd ratio (OR) of the diabetics to HT is 6.16. Among the obese persons, HT is present at (40.8%) vs. (30.2%) among the subjects of normal weight (p < 0.05). The OR of the obese to HT is 1.6. In conclusion, our results show a high frequency of HT in the east of Morocco; it affects nearly one third of the adult population aged 40 years and older. The relations between type 2 diabetes and obesity have also been identified and estimated.

Nemesure *et al.* (2006) studied hypertension, type 2 diabetes, and blood groups in a population of African ancestry. Elevated diastolic blood pressure was positively associated with years of age (odds ratio [OR] 1.03, 95% CI 1.02–1.05) the Rhesus D+ antigen (OR 2.68, 95% CI 1.21–5.97) and body mass index (OR 1.53, 95% CI 1.19–1.96), but negatively associated with the ABO blood group A allele (OR 0.68, 95% CI .48–.97). The likelihood of diabetes increased with years of age (OR 1.03, 95% CI 1.01–1.04), hypertension (OR 1.56, 95% CI 1.10–2.20), body mass

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index (OR 1.68, 95% CI 1.29–2.20), and waist-hip ratio (OR 1.36, 95% CI 1.05– 1.75), but decreased with presence of the Rhesus C+ antigen (OR .66, 95% CI .44–.97). Conclusions: The associations of diabetes and hypertension to these blood groups support possible genetic influences on both conditions in this and similar African-origin populations; however, further investigations in other settings are necessary to more fully elucidate these findings. logistic regression analyses was used.

Okoduwa et al. (2013) researched into the relationship of oxidative stress with type 2 diabetes and hypertension. The study involved 200 subjects (aged 20 to 79 years) divided into four groups of 50 subjects each. Non Diabetic Normotensive Persons (NDNP) as controls, while Diabetic Normotensive Patients (DNP), Non Diabetic Hypertensive Patients (NDHP) and Diabetic Hypertensive Patients (DHP) as cases. Biomarkers of oxidative stress were correlated with some trace mineral elements in serum samples collected from all the subjects. A significant (p < 0.01) negative correlation was observed between the following: CAT/MDA and Fe2+/MDA in the 3 case groups; SOD/MDA, GSH/MDA in both DNP and DHP groups; Vitamin C/MDA, Se2+/MDA and Zn2+/MDA in both NDHP and DHP groups. The negative correlation of Vitamin E with MDA was found to be significant (p < 0.01) only in DHP group. The relationship between biomarkers of oxidative stress and trace mineral elements obtained in their study is implicated in the changes in antioxidant defense system which resulted in the pathophysiologic mechanisms underlying the complication of type 2 diabetes and associated hypertension.



#### 2.3 Review of Medical Researches using Time Series Methods

Suleman and Sarpong (2011) modeled hypertension cases in Navrongo, Ghana, West Africa using Autoregressive Integrated Moving Average (ARIMA) stochastic model popularized by Box –Jenkins (1976). Their study showed that ARIMA (1,1) and ARIMA (3,2) models were adequate for modeling and forecasting admissions and outpatient cases respectively.

Karim *et al.* (2003) modeled type 1 diabetes using patients clinically data to develop two time series models in Jordan. The time series models were the Autoregressive with exogenous input (ARX) and Autoregressive Moving Average with exogenous input (ARMAX). The results showed that the ARX was better than the ARMAX in terms of predicting future values of glucose concentration.

Ekezie *et al.* (2014) conducted a research to model and forecast malaria mortality rate using Seasonal Autoregressive Integrated Moving Average (SARIMA) models at Aboh Mabaise General Hospital, Imo state Nigeria. They used the Box-Jenkins methodology to build ARIMA model for malaria mortality rate for the period. They concluded that the forecasted results revealed a decreasing pattern of malaria mortality in the last quarter of the year 2014.

Myriam *et al.* (2011) conducted a time series analysis of dengue incidence in Guadeloupe, French West Indies to forecast using climate variables as predictors. They used the Box- Jenkins approach to fit a Seasonal Autoregressive Integrated Moving Average (SARIMA) to model the incidence of the dengue from 2000 to 2006 using clinical suspected cases. They concluded that temperature improves



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dengue outbreak forecasts better than humidity and rainfall. The SARIMA model used climate data as independent variables and incorporated it into an early and a reliably monitoring system of dengue outbreak.

Also, Doherty and Graves (2015) modeled the Time-Series Analysis of Continuously monitored blood glucose and daily lifestyle. They used 40 patients with diabetes, continuously monitored blood glucose, food/medicine intake and patient activity/location tracked using global positioning system over a 4-day period. The Autoregressive Integrated Moving Average (ARIMA) model revealed a wide variety of blood glucose correlating factors related to specific activity types, locations and travel modes, although the impact was highly personal. Tradition variables related to food intake and medication were less often significant. The study revealed considerable patient by patient variation in the effects of geographic and daily lifestyle factors. They suggested that the map of blood glucose spatial variation or an interactive messaging system could provide new tools to engage patients and highlight potential risk factors.

Mevlut and Imran (2006) conducted a study to compare four different time series methods to forecast hepatitis A virus infection. In the study, they compared time series predictions capabilities of three artificial neural networks (ANN) algorithm multi-layer perception (MLP), radial basis function (RBF) and time delay neural network (TDNN) and autoregressive integrated moving average (ARIMA) model to forecast hepatitis A virus. To assess the effectiveness of these methods, a 13year time series monthly data of hepatitis A virus was used, in Turkey and the

results showed that MLP was were accurate and performed better than RBF and ARIMA model.

Alberto *et al.* (2007) modelled the incidence of malaria cases in Karuzi; Burundi using monthly malaria cases from local health facilities, data from rain and temperature records and normalized difference vegetation index. They used ARIMA model to show the relation between monthly malaria cases environmental variables.

Luz *et al.* (2008) used the Box-Jenkins approach to fit an autoregressive integrated moving average (ARIMA) model to dengue incidence in Rio de Janeiro, Brazil. The fitted model was used to predict dengue incidence for the year 2005. In fitting the model two approaches were used; 12-steps ahead 1-step ahead and the calculations showed that the 1-step approach ahead for predicting dengue incidence provided significantly more accurate predictions than the 12-step approach. They concluded that ARIMA models are useful tools for monitory dengue in Rio de Janeiro.

QiLi *et al.* (2012) also used the Box-Jenkins approach to fit an autoregressive integrated moving average (ARIMA) model to the incidence of hemorrhagic fever with renal syndrome in China from 1986 to 2009. The fitted model was used to predict hemorrhagic fever with renal syndrome incidence during 2010, and the number of cases from January to December 2010 fell within the model confidence interval. They concluded that the ARIMA model fits the fluctuation in



hemorrhagic fever with renal syndrome frequency and could be used to forecast hemorrhagic fever with renal syndrome cases in China.

Varun *et al.* (2014) forecasted malaria cases using climatic factors in Delhi, India. Monthly malaria cases from January 2006 to December 2013 were used to fit an autoregressive integrated moving average (ARIMA) model. The model explained 72.5% variability in the time series data. They concluded that ARIMA models of time series analysis is simple and reliable for forecasting malaria cases in Delhi, India.

Aboagye-Sarfo *et al.* (2013) also study to forecast HIV cases in the Ashanti Region of Ghana. In their study they used the Holt's exponential smoothing and the Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) model of time series analysis. The study revealed that the Holt's exponential smoothing predicted 2580 new HIV cases per year where as the Box-Jenkins autoregressive integrated moving average (ARIMA) model predicted 2556 number of new HIV cases per year in the Ashanti Region and they concluded that the HIV cases for the Ashanti Region will relatively be stable for the next three years.

Yury (2011) modeled alcohol consumption and suicide rates in Russia from 1980 to 2005 using Autoregressive Integrated Moving Average (ARIMA). The study revealed that alcohol consumption was significantly associated with both male and female suicides rates and that alcohol played a crucial role in the fluctuation in mortality rates in Russia.



William *et al.*(2013) also used interrupted time series Analysis to model the effects of the 2006 Russian Alcohol Policy on alcohol-related mortality. They used the Autoregressive Integrated Moving Average (ARIMA) to model the impact of the policy on the number of monthly deaths of the aged 15 years and above due to alcohol poisoning, alcohol cardiomyopathy, alcohol liver cirrhosis and alcohol-related mental disorders from 2000 to 2010. The study revealed that the policy was responsible for an annual decline of alcohol poisoning.

#### **2.4 Conclusion**

The chapter dealt with reviewing of literature that is relevant to the study. Reviewing of the literature has exposed us to the diverse techniques that researchers have employed in modeling the dynamic relationship between hypertension and diabetes cases. However, among the diverse techniques reviewed the Vector Autoregressive model was employed in this study to model the dynamic relationship between hypertension and diabetes cases in Northern Region because they were the techniques used frequently in literature for modeling dynamic relationship.



## CHAPTER THREE

#### **METHODOLOGY**

#### 3.0 Introduction

This chapter focuses on the source of the data collected for the research and the various statistical techniques employed in analyzing the data in order to meet the set objectives. It looks at both univariate and multivariate time series modelling techniques and diagnostics checking of estimated models.

#### 3.1 Data and Source

This study used secondary data on hypertension and diabetes cases from January 2006 to December 2014 obtained from the Tamale Teaching Hospital (TTH) database. The data for this research was analyzed with R, Gretl, STATA, and Minitab statistical packages.

#### **3.2 Trend Analysis**

The trend of a series reflects the long term growth or decline of the time series over time. A time series variable may exhibit different type of trends; the linear, quadratic, linear constant growth and quadratic constant growth trend models among others. This study estimated these four different trend models for the diseases under consideration.

A time trend in a time series is a linear function of time t, if the model is given by;

$$Y_t = \alpha_0 + \alpha_1 t + u_t \tag{3.1}$$

If the series exhibit quadratic trends, the model is given as;

$$Y_t = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + u_t \tag{3.2}$$

If the trend has a constant growth form, the model is given as;

$$Y_t = \alpha_0 e^{\alpha_1 t} u_t \tag{3.3}$$

and for a quadratic constant growth, the logarithmic form of the model is given as;

$$\ln Y_t = \ln \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \ln u_t$$
(3.4)

where  $Y_t$  is the actual value at time t, t = 1, ..., T,  $u_t$  is the error term and  $\alpha_0$ ,  $\alpha_1, \alpha_2$  are the regression coefficients.

#### 3.3 Unit Root Test

It is essential to establish the presence or absence of a unit root test in time series data analysis. The presence or absence of unit roots is imperative to identifying the nature of the processes that generate the time series data and to investigate the order of integration of the series. This is because, contemporary econometrics has indicated that, regression analysis using non-stationary time series variables produce spurious regression since standard results of ordinary least squares do not hold. A variable is said to be covariance or weakly stationary if the first two moments of the series; the mean and the autocovariance are finite and are time invariant.

In the absence of unit root, the time series fluctuates around a constant long-run mean with finite variance which does not depend on time. There are a number of proposed quantitative methods of testing for stationarity of a time series variable.



This study however employed one quantitative method in addition to the time series plots, Autocorrelation functions (ACF) and Partial Autocorrelation functions (PACF) graphical approaches. In graphical form, a time series plot which do not show mean reversion gives an indication that the levels of the series are non-stationary. Also, a slow decaying ACF plots also gives an indication of non-stationarity of a time series. The quantitative method used in this research is the Augmented Dickey-Fuller (ADF) test.

#### 3.3.1 Augmented Dickey Fuller (ADF) Unit Root Test

The Augmented Dickey-Fuller (ADF) test was employed in the study to determine whether the individual diseases contained a unit root (non-stationary) or were covariance stationary. The ADF test proposed by Dickey and Fuller (1979) was an upgraded form of the Dickey-Fuller (DF) test. This test is based on the assumption that the series follow a random walk with model;

$$Y_t = \phi Y_{t-1} + u_t \tag{3.5}$$

and tests the hypothesis:

 $H_0: \Phi = 1$  (Non\_stationary) against

 $H_1: \Phi < 1$ (Stationary)

where  $\Phi$  is the characteristic root of an AR polynomial and  $u_t$  is an uncorrelated white noise series with zero mean and constant variance  $\sigma^2$ . When  $\Phi = 1$ , equation (3.5) does not satisfy the weakly stationary condition of an AR (1) model hence the series becomes a random walk model known as a unit root nonstationary time series. Subtracting  $Y_{t-1}$  from both sides of equation (3.5) we have



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$$\Delta Y_t = \varphi Y_{t-1} + u_t, \quad t = (1, \dots, T)$$
(3.6)

where  $\varphi = \Phi - 1$ , and  $\Delta Y_t = Y_t - Y_{t-1}$ . For estimating the existence of unit roots using equation (3.6), we test hypothesis  $H_0: \varphi = 0$  against  $H_1: \varphi \neq 0$ . Under  $H_0$ , if  $\varphi = 0$ , then  $\Phi = 1$ , thus the series has a unit root hence is non-stationary. The rejection or otherwise of the null hypothesis,  $H_0$  is based on the *t*-statistic critical values of the Dickey Fuller statistic. The Dickey-Fuller test assumes that the error terms are serially uncorrelated, however, the error terms of the Dickey-Fuller test do show evidence of serial correlation. Therefore, the proposed ADF test includes the lags of the first difference series in the regression equation to make  $u_t$  a white noise. The Dickey and Fuller's (1979) new regression equation is given by;

$$\Delta Y_{t} = \varphi Y_{t-1} + \sum_{j=1}^{p} \gamma_{j} \Delta Y_{t-j} + u_{t}, \qquad t = (1, \dots, T)$$
(3.7)

If the intercept and time trend  $(\beta + \alpha t)$  are included, then equation (3.7) is written as;

$$\Delta Y_{t} = \beta + \alpha t + \varphi Y_{t-1} + \sum_{j=1}^{p} \gamma_{j} \Delta Y_{t-j} + u_{t}, \quad t = (1, \dots, T) \quad (3.8)$$

where  $\beta$  is an intercept,  $\alpha$  defines the coefficient of the time trend factor,  $\sum_{j=1}^{p} \gamma_j \Delta Y_{t-j}$  defines the sum of the lagged values of the response variable  $\Delta Y_t$ and p is the order of the autoregressive process. If  $\varphi$  of the Augmented Dickey Fuller model is zero (0), then there exist a unit root in the time series variable considered, hence the series is not covariance stationary. The choice of the starting augmentation order depends on the periodicity of the data, the



significance of  $\gamma_i$  estimates and the white noise residuals series  $u_t$ . The ADF test statistic is given by;

$$F_{\tau} = \hat{\varphi} / SE(\hat{\varphi}) \tag{3.9}$$

where  $\hat{\varphi}$  is the estimate of  $\varphi$  and  $SE(\hat{\varphi})$  is the standard error of the least square estimate of  $\hat{\varphi}$ . The null hypothesis  $(H_0)$  is rejected if, the  $p-value < \alpha$  (significance level). If the series is not stationary, it is transformed by differencing to make it stationary and stationarity tested again. If the time series is not stationary but its first difference is stationary, then the series is said to be an integrated process of order one (1) or simply an I(1) process.

#### 3.4 Vector Autoregressive (VAR) Modelling

A vector autoregression (VAR) model is a mechanism that is used to link multiple stationary time series variables together and it is an extension of the univariate autoregression (AR) model to dynamic multiple time series. The VAR model is useful for describing the dynamic behaviour and relationship between multiple time series, for forecasting the series and for structural analysis. The VAR model fits a time series regression of each dependent variable on its lag values and on the lag values of other dependent variables considered. Forecast from VAR models are quite flexible because they can be made conditional on the potential future paths of specified time series variables in the model. If the variables are not individually covariance stationary, it can be differenced to make it stationary and

then a VAR model is fitted to the stationary series. A VAR process consists of a set of k – endogenous time series variables

 $Y_t = (y_{1t}, y_{2t}, \dots, y_{kt})'$  for  $k = 1, \dots, K$ . A VAR model of order p denoted as VAR (p) is given by;

$$Y_t = v + A_1 y_{t-1} + \dots + A_p y_{t-p} + u_t, \quad t = 0, 1, \dots, T \quad (3.17)$$

where  $Y_t = (y_{1t}, \dots, y_{kt})'$  is a  $(k \times 1)$  random vector of the rates,  $A_i, i = 1, \dots, p$  is a fixed  $(K \times K)$  parameter (coefficient) matrices,  $v = (v_1, \dots, v_k)'$  is a fixed  $(K \times 1)$  vector of intercept allowing for the possibility of a zero mean and  $u_t = (u_{1t}, \dots, u_{kt})'$  is a K-dimensional white noise series or innovation process with time invariant positive definite covariance matrix and zero mean. It is assumed that  $u_t$  has a multivariate normal distribution.

#### 3.4.1 Lag Order Selection

In fitting a VAR (p) model, one important step is the determination of the optimal lag of the VAR process. Lag order determinations enable us to ensure that the model chosen will reflect the observed process as precisely as possible with a small error term. In this study, we consider three lag order selection methods which differ by the severity of the penalty imposed for parameter profligacy and hence in the parsimony of the model selected. This study used the Akaike Information Criterion (AIC) (Akaike, 1974), the Schwarz Bayesian Information Criterion (SBIC) (Schwarz, 1978) and the Hannan-Quinn Information Criterion (HQIC) (Hanan and Quinn, 1979) to determine the optimum lag order for fitting

the VAR (p) model that describe the relationship between the set of time series variables. These criteria are given by;

$$AIC = ln \left| \widehat{\Sigma_u(p)} \right| + \frac{2}{T} p K^2$$
(3.26)

$$HQIC = ln \left| \widehat{\sum_{u}(p)} \right| + \frac{2 ln \{ln(T)\}}{T} p K^{2}$$
(3.27)

$$SBIC = \ln \left| \widehat{\Sigma_u(p)} \right| + \frac{\ln(T)}{T} p K^2$$
(3.28)

where T denotes the number of observations in the data, p assigns the lag order,  $\widehat{\Sigma_{u}(p)} = T^{-1} \sum_{t=1}^{T} \widehat{u_t u_t}$  is the residual covariance matrix without a degree of freedom corrected from the model and K is the number of parameters in the statistical model. For all the criteria, p is chosen so that the value of the criterion is minimized. The first part of these criteria measures the goodness of fit of the statistical model to the data whiles the second part is the penalty term of the criteria which penalizes a candidate model for the number of parameters used. Based on this penalty term, the SBIC and HQIC are consistent estimators and turns to select models with fewer parameters when the sample size is large than does the AIC. The lag order with the least values of these criteria is the optimum number of lags to be used.

#### 3.4.2 Stability Condition of a VAR (p) Model

Statistical inference using a VAR (p) model depends crucially on the stability of the model parameters over time. Given sufficient starting values, a stable VAR (p)process generates stationary time series with time invariant means, variances and



a,

covariance structure. The stability is determined by evaluating the reverse characteristic polynomial equation of the VAR (p) model given as;

$$det(l_k - A_1 z^1 - \dots - A_p z^p) \neq 0, \ for \ |Z| \le 1$$
(3.29)

The VAR (p) process is stable if the reverse characteristic polynomial has no root in and on the complex unit circle (thus the process is stable if |z| > 1 (Lutkepohl, 2005)). If the solution of the reverse characteristic polynomial has a root z = 1, then either some or all the variables in the VAR (p) process are integrated of order one (l(1)). In practice, if the eigenvalues of the parameter matrix,  $A_i$  are less than one (1) in modulus, then the VAR (p) is stable (which is  $|A_i| < 1$  in univariate case). The stability of the VAR (p) model enables us to write the VAR (p) process as an invertible moving average process from which further inference such as Impulse Response Analysis can be made.

#### **3.5 Model Diagnostics**

To use the fitted models for statistical inference, it is essential to diagnose the model to determine whether the model best fit the series. This involves checking whether or not the residuals of the model fitted are white noise series; thus whether they are free from serial correlation and conditional heteroscedasticity. This study employed both univariate and multivariate model diagnostics techniques such as the univariate and multivariate Ljung-Box, the univariate and multivariate ARCH-LM as well as the CUSUM test to diagnose the fitted model.



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#### 3.5.1 Univariate Ljung-Box Test

The study employed the univariate Ljung and Box (1978) test to test jointly whether or not several autocorrelations  $(r_l)$  of the residuals of the individual VAR (p) models fitted were zero. It is based on the assumption that the residuals contain no serial correlation (no autocorrelation) up to a given lag m. The univariate Ljung-Box statistic is given by:

$$Q(m) = T(T+2)\sum_{l=1}^{m} \frac{r_l^2}{T-l}$$
(3.30)

where  $r_l$  represents the residual sample autocorrelation at lag l, T is the size of the series, m is the number of time lags included in the test. Q(m) has an approximately chi-square distribution with m degrees of freedom. We fail to reject H<sub>0</sub> and conclude at  $\alpha$ -level of significance that, the residuals are free from serial correlation when the p-value is greater than the significance level.

#### 3.5.2 Univariate ARCH-LM Test

For a fitted model to adequately fit a series, the variance of the models' residuals must be constant over time. The univariate ARCH-LM test proposed by Engle (1982) was used in this research to check for the presence or absence of conditional heteroscedasticity in the residuals of the individual equations of the model fitted. If there exist no ARCH-effect, it implies that the residuals of the model have constant variance. This statistic uses the linear regression model;

$$u_t^2 = a_0 + a_1 u_{t-1}^2 + \dots + a_m u_{t-m}^2 + e_t$$
(3.31)  
$$t = m + 1, \dots, T$$



where  $e_t$  is the error term, T is the sample size and m is a positive integer. The ARCH-LM statistic tests the hypothesis that;

 $H_0: a_1 = \cdots = a_m = 0$  (no ARCH – effect) against

 $H_1: a_1 \neq \cdots \neq a_m \neq 0$  (ARCH – effect exist)

The ARCH-LM test statistic is calculated as;

$$LM = TR^2 \tag{3.32}$$

where  $R^2$  is the coefficient of determination for the auxiliary regression. The decision rule is to reject  $H_0$  and conclude that there is conditional heteroscedasticity (ARCH-effect) in the residuals of the model if  $LM > \chi^2$  (m), or if the  $p - value < \alpha$ , where m is the lag order of ARCH-effect and  $\alpha$  is the significance level chosen.

#### 3.5.3 Multivariate Ljung-Box Test

In testing for the accuracy of the individual equations of the fitted model, it is important to test for the accuracy of the overall VAR (p) process. This research therefore employed the multivariate Ljung-Box test to check for the presence or absence of serial correlation among the residuals of the overall VAR (p) model. The test is design to test the hypothesis;

 $H_0: R_m = (R_1, \dots, R_m) = 0$  (no serial correlation) against

 $H_1: R_m \neq 0$  (there exist serial correlation in the residuals) The multivariate Ljung-Box test is given by;

$$Q_m = T^2 \sum_{i=1}^m (T-i)^{-1} tr(\hat{c}'_i \hat{c}_0^{-1} \hat{c}_i \hat{c}_0^{-1})$$
(3.33)



where  $\hat{c}_i = 1/T \sum_{t=i+1}^T \hat{u}_t \hat{u}'_{t-i}$ . If  $T \to \text{infinity}$ , then  $\frac{T}{T^2(T-i)^{-1}} \to 1$ . For large Tand m,  $Q_m \sim \chi^2(k^2(h-p))$ . We fail to reject  $H_0$  and conclude that there is no serial correlation in the residuals of the model when  $Q_m < \chi^2(k^2(h-p))$  or the *p*-value of the statistic is greater than the chosen  $\alpha$ -level.

#### 3.5.4 Multivariate ARCH-LM Test

The multivariate ARCH-LM test was also used to test for conditional heteroscedasticity on the residuals of the overall VAR (p) model. The multivariate ARCH-LM test is based on the regression model below;

vech  $(u_t u'_t) = a_0 + a_1 vech(u_{t-1}u'_{t-1}) + \dots + a_p vech(u_{t-p}u'_{t-p}) + e_t$  (3.34) where  $e_t$  assigns a spherical error process, vech is the column-stacking operator for symmetric matrices that stacks the columns from the main diagonal on

downward.

 $a_0$  is 1/2 k(k+1)-dimension and  $a_j$ 's are  $1/2 k(k+1) \times 1/2 k(k+1)$ coefficient matrices (j = 1, ..., p). The multivariate ARCH-LM statistic tests the pair of hypothesis;

- $H_0 = a_1 = \cdots = a_p = 0$  (No ARCH-effect) against
- $H_1 = a_1 \neq 0 \text{ or } \dots \text{ or } a_p \neq 0 \text{ (ARCH-Effect exist)}$

If all the  $a_j$  matrices are zero, there is no ARCH effect in the residuals of the model. The LM statistic can be determined by replacing all unknown  $u_t$ 's by estimated residuals from a VAR (p) model and estimating the parameters in the resulting auxiliary model by OLS. Denoting the residuals covariance matrix



estimator by  $\widehat{\Sigma_{vech}}$  and the corresponding matrix obtained for q = 0 by  $\Sigma_0^{-1}$ , the ARCH-LM statistic is given as;

$$LM_{ARCH(p)} = \frac{1}{2}TK(K+1) - Ttr(\widehat{\Sigma_{vech}} \Sigma_0^{-1})$$
(3.35)

The statistic has asymptotic  $\chi^2\left(\frac{pK^2(K+1)^2}{4}\right)$  distribution, where p the is the lag order of the process, k is the number of parameters and T is the size of the series.

#### 3.5.5 Cumulative Sum (CUSUM) Test

The cumulative sum test by Brown *et al.* (1975) was used to test for stability of the fitted model over time. The focus of this test is the maximal excursion (from zero) of the random walk defined by the cumulative sum of adjusted (-1, +1) digits in the sequence. The purpose of the test is to determine whether the cumulative sum of the partial sequences occurring in the tested sequence is too large or too small relative to the expected behavior of that cumulative sum for random sequences. The test statistic is defined as;

$$\text{CUSUM}_{\varphi} = \sum_{t=k+1}^{\varphi} \frac{q_t^{(r)}}{\partial_q}$$
(3.36)

where  $\hat{q}_t^{(r)}$  are the recursive residuals and  $\hat{\sigma}_q$  is the standard error of the regression fitted to all T sample points and  $\varphi = K + 1, ..., T$ . For a structural unstable (random) model, the CUSUM wanders off too far from the zero line. A test with a significance level of 5% is obtained by rejecting stability if CUSUM<sub>r</sub> crosses the lines  $\pm 0.948[\sqrt{T-K} + 2(\varphi - K)/\sqrt{T-K}]$  (Ploberger *et al.*, 1989).



The CUSUM test is designed basically to detect a non-zero mean of the recursive residuals due to shift in the model parameters.

#### 3.6 Causality Test

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The idea behind Granger causality is that, if a time series variable x affects another z, then, x should help improve the prediction of variable z. A stationary time series variable  $x_t$  is Granger causal for another stationary time series variable  $z_t$ , if past values of  $x_t$  have additional power in predicting  $z_t$  after controlling for past values of  $z_t$  (Gelper and Croux, 2007). If the innovation to  $z_t$  and the innovation to  $x_t$  are correlated, then there exist instantaneous causality. Causality may be classified as unidirectional, bilateral or independent (Gujurati, 2003). Mathematically, the process  $x_t$  is said to Granger cause  $z_t$  if;

 $\sum_{z} (h/\Omega_t) \leq \sum_{z} (h/\Omega_t) \{x_s | s \leq t\} \text{ for at least } h =$ 

1,2,..... (3.37) where  $\Omega_t$  is the information set containing all the relevant information in the universe available up to including t,  $z_t(h/\Omega_t)$  is the optimal h-step forecast of the process  $z_t$  at origin t base on the information in  $\Omega_t$ ,  $\sum_z (h/\Omega_t)$  is the forecast Mean Square Error (MSE) and  $(\Omega_t \setminus \{x_s \mid s \leq t\})$  is the set containing all relevant information in the universe except the information of past and present values of the  $x_t$  process. This implies that, with respect to  $x_t$ , the variance of the optimal linear predictor of  $z_{t+h}$  based on  $z_{t,}, z_{t-1}, \dots$  alone (Lukepohl, 2005).

#### 3.7 Impulse Response Function (IRF) Analysis

The Granger and Instantaneous causality tests introduced are quite useful to infer whether a time series variable helps predict another one. However, these analyses fall short of quantifying the impact of the impulse time series variable on the response variable over time. The impulse response analysis is used to investigate these kinds of dynamic interactions between the endogenous time series variables and is based upon the Wold's moving average representation of a VAR (p) process. IRF enables us to determine the response of one time series variable to an impulse or a shock in another time series variable in the system that involves a number of further variables as well. If there is a reaction of one time series variable to an impulse in another variable, then the latter is causal for the former. However, the effect of a unit shock in any of the variables dies away quite rapidly due to stability of the system. The Wold representation is based on the orthogonal errors  $\eta_t$  given by;

$$R_{t} = \mu + \Theta_{0}\eta_{t} + \Theta_{1}\eta_{t-1} + \Theta_{2}\eta_{t-2} + \dots$$
(3.38)

where  $\Theta_0$  is a lower triangular matrix. The impulse responses to the orthogonal shocks  $\eta_{jt}$  are;

$$\frac{\partial R_{i,t+s}}{\partial \eta_{j,t}} = \frac{\partial R_{i,t}}{\partial \eta_{j,t-s}} = \Theta_{ij}^s \quad i, j = 1, 2, \dots, k, s > 0$$
(3.39)

where  $\theta_{ij}^s$  is the (i, j)th element of  $\theta_0$ . For k variables there are  $k^2$  possible IRF.



#### 3.8 Forecast Error Variance Decomposition (FEVD) Analysis

The forecast error variance decomposition tells us the proportion of the movements in a sequenced due to its "own" shocks versus shocks to the other variable. The FEVD was used in this research to determine the contribution of the  $j^{th}$  variable to the *h*-step forecast error variance of the  $i^{th}$  variable. If the  $j^{th}$  variable shocks explain none of the forecast error variance of the  $i^{th}$  variable at all forecast horizons, then the  $i^{th}$  sequence is exogenous. Also, if the  $j^{th}$  variable shocks could explain all of the forecast error variance in the  $i^{th}$  sequence at all forecast horizons, then the  $i^{th}$  variable would be entirely endogenous. The FEVD is given as;

$$FEVD_{i,j}(h) = \frac{\sigma_{\eta_j}^2 \sum_{s=0}^{h-1} (\Theta_{i_j}^s)^2}{\sigma_{\eta_1}^2 \sum_{s=0}^{h-1} (\Theta_{i_j}^s)^2 + \dots + \sigma_{\eta_k}^2 \sum_{s=0}^{h-1} (\Theta_{i_k}^s)^2} \quad i, j = 1, 2, \dots, k$$
(3.40)

where  $\sigma_{\eta_j}^2$  is the variance of  $\eta_{jt}$ . A VAR (p) process with k variables will have  $k^2 FEVD_{i,j}(h)$  values.

## 3.9 Cross Validation of VAR (p) Model

The best model for further inference was cross validated using chi-square goodness of fit test. The Chi-square goodness of fit test is a statistical technique for comparing observed data with expected or predicted data according to a specified hypothesis. The chi-square statistic is given as;

$$\chi^{2} = \sum_{j=1}^{k} \frac{(O_{j} - E_{j})^{2}}{E_{j}}$$
(3.41)



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with k-1 degrees of freedom, where  $O_j$  is the observed value and  $E_j$  is the expected value and k is the number of rows in the forecasted data (sample size).

#### 3.10 The Likelihood Ratio Test (LRT)

Likelihood ratio test is a statistical test used to compare the goodness of fit of two models. Thus the null model and the alternative model. It compares the log likelihoods of the two models, if the difference is statistically significant, then the less restrictive model is said to fit the data significantly better than the more restrictive model. The likelihood ratio test is given as,

$$T_{LRT} = -2\left(\log \hat{L}_{reduced} - \log \hat{L}_{full}\right) = 2\log \hat{L}_{full} - 2\log \hat{L}_{reduced} (3.42)$$

This test statistic approximately follows a chi-square distribution

#### **3.11 Conclusion**

This chapter gave a detailed account of the statistical techniques employed in this study for analyzing the data in order to achieve the set objectives.



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## **CHAPTER FOUR**

## **ANALYSIS AND DISCUSSION OF RESULTS**

#### **4.0 Introduction**

This chapter analyses, interprets and discusses the results of the study. The chapter is organised into preliminary analysis, further analysis and discussion of the results obtained.

#### 4.1 Preliminary Analysis

This section presents and explains the descriptive statistics of hypertension and diabetes cases. From Table 4.1, it was clear that the diabetes cases have a larger variability than the hypertension cases for the entire period under consideration as evident by the coefficient of variation (CV) of 90.71% and 41.46% respectively. The minimum (Min) and maximum (Max) number of diabetes cases for the entire period was 1.0 and 88.0 respectively and that of hypertension cases were 34.0 and 262.0 respectively. Both the diabetes and hypertension cases were positively skewed for the entire period. The diabetes cases have a positive excess kurtosis of 1.62 indicating a leptokurtic shape and the hypertension cases have a negative excess kurtosis of -0.66 exhibiting a platykurtic shape. The Shapiro-Wilk test of normality revealed that, the two diseases were not normally distributed, since a significant test statistic was obtained at the 5% significance level.



	Diseases	
Statistic	Diabetes	Hypertension
Mean	20.94	126.62
CV (%)	90.71	41.46
Min	1.00	34.00
Max	88.00	262.00
Skewness	1.38	0.42
Kurtosis	1.62	-0.66
Shapiro-Wilk test	0.86	0.97
Probability	0.00**	0.01**

#### Table 4.1: Descriptive statistics of diabetes and hypertension cases

\*\*: Means normality was rejected at 5% significance level

An investigation of the diabetes and hypertension cases for the various months revealed that, the highest average diabetes (25.56) and hypertension (144.1) cases occurred in the months of July and March respectively as shown in Table 4.2 and 4.3. The least average diabetes (17.44) and hypertension (103.7) occurred in the months of April and October respectively. In terms of the minimum and maximum diabetes cases, the month of April, December and November have the minimum diabetes cases and the month of July recorded the maximum diabetes cases. The minimum and maximum hypertension cases occurred in the month of November. The diabetes cases for the various months were all positively skewed. For the hypertension cases, the months of January, November and December were negatively skewed while the other months were positively skewed.

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Month	Mean	Min	Max	CV (%)	Skewness	Kurtosis
Diabetes						
January	20.56	2.00	53.00	92.98	0.75	-1.04
February	17.67	2.00	64.00	105.33	2.32	5.93
March	21.56	2.00	69.00	92.73	1.91	4.31
April	17.44	1.00	36.00	79.49	0.03	-2.02
May	23.56	4.00	59.00	72.92	1.04	1.18
June	21.67	3.00	71.00	102.24	1.65	2.52
July	25.56	2.00	75.00	92.10	1.18	1.35
August	25.67	7.00	88.00	102.19	2.06	4.25
September	22.33	4.00	70.00	93.15	1.70	3.20
October	19.67	3.00	59.00	88.95	1.51	2.83
November	17.67	1.00	59.00	114.61	1.21	0.71
December	17.89	1.00	41.00	85.39	0.35	-1.61

## Table 4.2: Monthly descriptive statistics of diabetes



Hypertensio	n	2 <u>-1115 - 1115 - 1115 - 1115 - 1115 - 1115 - 1115 - 1115 - 1115 - 1115 - 1115 - 1115 - 1115 - 1115 - 1115 - 1115</u>				<u> </u>
January	131.00	50.00	203.00	41.14	-0.02	-1.32
February	122.40	55.00	193.00	42.46	0.34	-1.50
March	144.10	56.00	227.00	38.11	0.03	-0.54
April	121.70	59.00	189.00	37.51	0.05	-1.32
May	131.80	67.00	238.00	42.96	0.93	0.11
June	134.80	52.00	214.00	42.45	0.00	-1.35
July	134.00	66.00	212.00	37.54	0.51	-1.03
August	134.30	79.00	225.00	35.96	0.66	-0.11
September	109.90	54.00	241.00	50.14	1.85	4.51
October	103.70	51.00	200.00	50.08	1.31	0.37
November	139.30	34.00	262.00	55.39	-0.11	-0.95
December	112.40	50.00	156.00	30.38	-0.74	-0.01

## Table 4.3: Monthly descriptive statistics of hypertension cases

The time series plot in Figure 4.1 depict that, the diabetes and hypertension cases over the entire period fluctuated with time.



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Figure 4.1: Time series Plots of Diabetes and Hypertension cases

The nature of trend characterizing the diabetes and hypertension cases over time was investigated using the Linear, Quadratic, Log-linear and Log-quadratic time trend models. The results as depicted in Table 4.4, revealed that both the diabetes and hypertension cases were best modeled by the log-linear trend model; since the log-linear model had the smallest value of AIC, BIC and HQIC.



Model	AIC	BIC	HQIC
Diabetes	<u> </u>	<u>.</u>	
Linear	893.93	899.29	896.10
Quadratic	894.22	902.26	897.48
Log-linear	281.77 <sup>*</sup>	287.13 <sup>*</sup>	283.95 <sup>*</sup>
Log-quadratic	281.81	289.85	285.07
Hypertension			
Linear	1164.62	1169.99	1166.8
Quadratic	1165.07	1173.12	1168.33
Log-linear	132.06*	137.97*	134.78*
Log-quadratic	132.61	140.10	135.32

Table 4.4: Trend analysis of diabetes and hypertension cases

\*: Means best based on the model selection criteria.

The parameters of the log-linear trend models for the diabetes and hypertension cases were estimated as shown in Table 4.5. The parameters of the individual trend models were statistically significant at the 5% significance level; thus the parameters significantly account for the variation in the diabetes and hypertension cases.



	<b>Table 4.5: Estimates</b>	of the log-linear	• model for diabetes	and hypertension
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Model	Coefficient	Std. Error	<i>t</i> -ratio	<i>p</i> -value
Diabetes				
Constant	1.5102	0.1713	8.8181	0.000**
Time (t)	0.0195	0.0027	7.1497	0.000**
Hypertensi	on	<u></u>	<u> </u>	·····
Constant	4.8418	0.0859	56.3982	0.0000**
Time (t)	-0.0017	0.0014	-1.2414	0.0200**

# cases

\*\*: Means significant at the 5% significance level.

Hence, the estimated log-linear trend models for the diabetes and hypertension cases are given as;

Diabetes;	$\ln Diabetes = 1.5102 + 0.0195t$	(4.1)
Hypertension;	$\ln Hypertension = 4.8418 - 0.0017t$	(4.2)

## **4.2 Further Analysis**

In this section, the dynamic relationship between diabetes and hypertension cases was investigated using Vector Autoregressive (VAR) model. A total of 95 data points were used in fitting the models while the remaining 12 data points were used for cross validation of the fitted model.



#### 4.2.1 Unit Root Test of the Series

To fit the VAR model, it is imperative to investigate the order of integration of both series. From Table 4.1, the descriptive statistics revealed that there are large swings in the data indicating non-stationarity. This can be seen from the coefficient of skewness and kurtosis of both the diabetes and hypertension cases. The non-stationarity of both series can be affirmed from the slow decay of the ACF plots of both diabetes and hypertension cases and very dominant spike at lag 1 of the PACF plots of both series (Figure 4.2 and Figure 4.3). This gives a graphical indication that the levels of the series were not stationary.



Figure 4.2: ACF and PACF plots of diabetes cases





Figure 4.3: ACF and PACF plots of hypertension cases

To further confirm the non-stationarity of the levels of both series, a unit root test was conducted. As shown in Table 4.6, an insignificant Augmented Dickey-Fuller (ADF) test statistic was obtained for both series at the 5% significance level when the test was performed with either a constant or a constant with time trend. This affirms the existence of unit roots in the levels of both diabetes and hypertension cases.



	Only Constant		Constant and Trend		
Category	Test Statistic	<i>p</i> -value	Test Statistic	<i>p</i> -value	
Diabetes	-1.47861	0.5447	-3.44961	0.4502	
Hypertension	-2.30267	0.1711	-2.2917	0.4379	

	Fable 4.6: ADF	test of (	diabetes and	l hypertension	cases in	level form
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Both series were logarithmically transformed and first differenced and tested for stationarity using the ADF test. The results as shown in Table 4.7, clearly indicates that the diabetes and hypertension cases were both significant.

Ta	ble	4.7:	ADF	test of	transformed	first	differenced	series

	Only Constant	·	Constant and Trend		
Category	Test Statistic	<i>p</i> -value	Test Statistic	<i>p</i> -value	
Diabetes	-4.31612	0.00041**	-4.30909	0.00298**	
Hypertension	-4.02157	0.001303**	-4.03172	0.00785**	

\*\*: Means significant at the 5% significance level

## 4.2.2 Fitting VAR Model

The dynamic relationship between the diabetes and hypertension cases was investigated by fitting Vector Autoregressive (VAR) model. Since the original series were not covariance stationary, the transformed first differenced series were used in fitting the VAR model. To determine the optimal maximum lag order, p to be included in fitting the VAR model, four lag order selection criteria were used.



The results are shown in Table 4.8, revealed that, the Final Prediction Error (FPE), AIC, HQIC selected lag two (2) and BIC selected lag one (1).

Table 4.8: lag Order Selection for Fitting VAR Model

Lag	FPE	AIC	HQIC	BIC
1	0.0649	2.9408	3.0148	3.1262*
2	0.0605*	2.8701*	2.9935*	3.1791
3	0.0623	2.8994	3.0721	3.3320
4	0.0649	2.9389	3.1610	3.4951
5	0.0699	3.0104	3.2818	3.6902
6	0.0752	3.0817	3.4025	3.8851
7	0.0765	3.0949	3.4650	4.0219
8	0.0817	3.1555	3.5750	4.2061
9	0.0823	3.1562	3.6251	4.3304
10	0.9000	3.2369	3.7551	4.5347
11	0.0961	3.2924	3.8600	4.7138
12	0.1027	3.3467	3.9636	4.8917

\*: Means best based on model selection criteria

Both VAR (1) and VAR (2) models were fitted to the transformed differenced series, and the Likelihood Ratio Test (LRT) used to select the best model for investigating the dynamic relationship. From Table 4.9, the significant likelihood ratio test statistic revealed that the VAR (2) was best for modeling the dynamic relationship.



Model	FPE	AIC	HQIC	BIC
VAR (1)	0.0609	2.8683	2.912	2.9765*
VAR (2)	0.0575*	2.8205*	2.9085*	3.0383
Likelihood Ratio Test Statistic= 13.2945			<i>p</i> -value= 0.0099**	

## Table 4.9: Model Selection Criteria

Electrologi Ratio Test Statistic = 15.2945 p-value = 0.0099

\*: Means best based on model selection criteria

\*\*: significant at the 5% significance level

VAR (2) model was therefore fitted to determine the dynamic relationship between diabetes and hypertension cases. From Table 4.9, the results revealed that lag one (1) of hypertension and diabetes are statistically significant at the 5% significance level in predicting hypertension cases. However, lag 10f hypertension is not statistically significant in predicting diabetes cases. Both lag 1 and lag 2 of diabetes are useful in predicting diabetes cases whiles lag 2 of hypertension is statistically significant in predicting diabetes but not hypertension.


Equations	Variables	Coefficients	Std. Error	t-ratio	<i>p</i> -value
Diabetes	Hypertension.L1	0.2245	0.2801	0.8015	0.4250
	Hypertension.L2	0.5583	0.2719	2.0536	0.0430**
	Diabetes.L1	-0.6059	0.1077	-5.6281	$0.0000^{**}$
	Diabetes.L2	-0.3147	0.1112	-2.8289	0.0058**
Hypertension	Hypertension.L1	-0.3969	0.1134	-3.4989	$0.0007^{**}$
	Hypertension.L2	-0.0895	0.1101	-0.8128	0.4185
	Diabetes.L1	-0.0899	0.0436	-2.0613	0.0422**
	Diabetes.L2	0.0190	0.0451	0.4227	0.6735
FPE = 0.0575	AIC = 2.8205	HQIC = 2.9085			
BIC = 3.0383	Log-likelihood = -12	3.153			

# Table 4.10: Parameter estimates of VAR (2) Model

\*\*: Means significant at the 5% significance level

The estimated VAR (2) model without an intercept is given by;

$$\begin{bmatrix} Diabetes_t \\ Hypertension_t \end{bmatrix} = \begin{bmatrix} -0.6059 & 0.2245 \\ -0.0899 & -0.3969 \end{bmatrix} \begin{bmatrix} Diabetes_{t-1} \\ Hypertension_{t-1} \end{bmatrix} + \begin{bmatrix} -0.3147 & 0.5583 \\ 0.0190 & -0.0895 \end{bmatrix} \begin{bmatrix} Diabetes_{t-2} \\ Hypertension_{t-2} \end{bmatrix} + \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix}$$
(4.3)

Table 4.11 shows additional information about each individual equation. It is clear that each individual time series model fitted for the diabetes and hypertension cases is statistically significant at the 5% significance level as indicated by the F-statistic.



Equation	F-statistic	<i>p</i> -value
Diabetes	8.8617	0.0000**
Hypertension	8.3592	0.0000**

#### Table 4.11: Test for Significance of the Equations of the VAR (2) Model

\*\*: Means significant at the 5% significance level

The stability of the VAR (2) model was also investigated. From Table 4.12, the results revealed that the parameters of the VAR (2) model were structurally stable over time as all the eigen values of the parameters have modulus less than one (1). This affirms that the transformed series used in fitting the VAR model were weakly stationary as required in fitting a VAR model.

## Table 4.12: VAR (2) Model Stability test

Eigenvalues	Modulus
-0.2253361+0.5639056i	0.607261
-0.2253361-0.5639056i	0.607261
-0.4430372	0.4430372
-0.1110038	0.1110038

The stability of the VAR (2) model was further investigated using the CUSUM test. From Figure 4.4., the CUSUM plot of the residuals of each model falls within the 95% confidence limit indicating that, their individual residual mean are not significantly different from zero and have constant variance. This affirms that



the parameters of each model were structurally stable over time. This clearly shows that, the VAR (2) model fitted provides an adequate representation of the short run relationship between the diabetes and hypertension cases.



Figure 4.4: CUSUM Plots of the Individual Equations of the VAR (2) Model

To ensure that the fitted VAR (2) model is adequate, both univariate and multivariate model diagnostic tests were performed. The univariate Ljung-Box test and ARCH-LM test as shown in Table 4.13 revealed that the individual equations of the VAR (2) model were free from serial correlation and conditional heteroscedasticity at lag 12, 24 and 36 respectively since the p-values of all the test statistics were insignificant at the 5% significance level. This implies that the



residuals of the models were uncorrelated, thus have zero mean and constant variance over time; hence are white noise series.

	Ljun	g-Box Test		ARCH-LM Test	
Equation	Lag	Test Statistic	<i>p</i> -value	Test Statistic	<i>p</i> -value
	12	9.0895	0.6950	9.9348	0.6217
Diabetes	24	17.2323	0.8390	16.3982	0.8732
	36	32.4820	0.6370	29.0590	0.7872
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	12	15.3590	0.2220	12.1014	0.4376
Hypertension	24	33.6992	0.0902	22.8598	0.5281
	36	43.4118	0.1850	39.8502	0.3028

Table 4.13: Univariate Ljung-Box Test and ARCH-LM Test

The adequacy of the overall VAR (2) model was also investigated using the multivariate Ljung-Box and ARCH-LM test as shown in Table 4.14. The results revealed that the residuals of the VAR (2) model were free from serial correlation and conditional heteroscedasticity as the p-values of the entire test statistic were insignificant at the 5% significance level. This implies that the residuals of the model were uncorrelated and have constant variance. The Jarque-Bera (JB) normality test revealed that the residuals of the VAR (2) model were normally distributed since the test statistic was insignificant at the 5% significance level.



This implies that all the necessary conditions of fitting a VAR model have been satisfied indicating the overall adequacy of the model.

Table 4.14: Multivariate Ljung-Box Test and ARCH-LM Test of VAR (2)

	Ljung-Box Test			ARCH-LM Test		
Equation	Lag	Test Statistic	<i>p</i> -value	Test Statistic	<i>p</i> -value	
	12	40.3719	0.4338	95.9151	0.7908	
VAR (2)	24	79.6793	0.7249	207.0000	0.6580	
	36	119.3904	0.8439	171.0000	1.0000	

The VAR (2) model was cross validated using the chi-square goodness of fit statistic. The results, as shown in Table 4.15 revealed that, there is no significant difference between the observed diabetes and hypertension cases and their forecasted values. This can be seen from the insignificant chi-square statistic obtained for the results of both models. This indicates that the fitted VAR (2) model produce values that mimic the behaviour of the diabetes and hypertension cases over time although the values of the observed and expected are not exactly the same.



Model	Chi-square $(\chi^2)$ statistic	Critical Value
Diabetes	17.243	19.675
Hypertension	16.518	16.675

Table 4.15: Chi-square Goodness (	of Fit Test of	of the VAR (2) Model
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Reject if  $\chi^2$  statistic > critical value

## 4.2.3 Causality Analysis

After the diagnostic tests revealed that the VAR (2) model was adequate, the model was used to investigate both Granger causality and instantaneous causality between diabetes and hypertension cases. The results of the Granger causality as shown in Table 4.16 revealed that diabetes Granger cause hypertension but the reverse is not true. This implies that there is a unidirectional relationship between diabetes and hypertension. Thus, if past diabetes cases are known then future hypertension cases can be predicted. Further, the instantaneous causality shown in Table 4.17 revealed that both diabetes and hypertension cases causes each other. The result clearly indicates that there is a bilateral relationship between diabetes and hypertension. This implies that the past values of diabetes are useful in predicting hypertension and the past values of hypertension are also useful in predicting diabetes.



Equations	Excluded	<b>Chi-squared</b>	Df	<i>p</i> -value
Hypertension	Diabetes	6.2281	2	0.044**
	All	6.2281	2	0.044**
Diabetes	Hypertension	4.3701	2	0.112
	All	4.3701	2	0.112

# **Table 4.16: Granger Causality Test**

\*\*: Means significant at the 5% significance level

### **Table 4.17: Instantaneous Causality Test**

Equation	Cause variable	Test Statistic	Df	<i>p</i> -value
Diabetes	Hypertension	12.3521	1	0.0004**
Hypertension	Diabetes	12.3521	1	0.0004**

\*\*: Means significant at the 5% significance level

## 4.2.4 Impulse Response Function (IRF) Analysis

The impulse response function explains how the diabetes and hypertension cases in the model interact with each other following a shock in the VAR (2) model. When the impulse variable was hypertension, the hypertension cases showed a negative reaction in the first period and then a positive reaction after the second period until a stable response was obtained after period five. The diabetes cases showed both negative and positive reaction within the first four periods and then a stable response after period five.



When the impulse variable was diabetes, the hypertension cases experienced a negative shock in the first two periods, a positive shock in the third period, negative shock in the fourth period and a positive shock in the fifth period until a stable response was obtained after the tenth period. The diabetes cases experienced a negative shock in the first two periods and a positive shock after period three, followed by a negative shock in period four with slight fluctuation after period five until a stable response was obtained.



Figure 4.5: Plot of Impulse Response Analysis

#### 4.2.5 Forecast Error Variance Decomposition (FEVD) Analysis

The variance decomposition was used to determine the proportion of forecast uncertainty in an endogenous variable that is explained by itself and by other endogenous variable in the study. Table 4.18 gives the FEVD of the hypertension cases. It was realised that, much of the forecast uncertainty in the hypertension cases have been explained by innovations in hypertension itself. For instance in



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the tenth period, about 91.53% of the forecast uncertainty in hypertension was explained by innovations in hypertension, whiles about 8.47% of the forecast uncertainties in hypertension have been explained by diabetes cases.

Period	Std. Error	Hypertension	Diabetes
1	0.311	100.000	0.000
2	0.352	96.731	3.269
3	0.363	92.414	7.586
4	0.365	91.576	8.424
5	0.365	91.587	8.413
6	0.366	91.540	8.460
7	0.366	91.541	8.460
8	0.366	91.531	8.469
9	0.366	91.527	8.473
10	0.366	91.527	8.473

Table 4.19 displays the FEVD of the diabetes cases. The diabetes cases explained about 84.29% of the forecast uncertainty in diabetes cases whiles the hypertension cases explained about 15.71% of the forecast uncertainty in diabetes cases. This clearly shows that the hypertension cases are useful in explaining an appreciable amount of the forecast uncertainty in the diabetes cases.

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Period	Std. Error	Hypertension	Diabetes
1	0.769	15.316	84.684
2	0.887	13.101	86.899
3	0.894	14.489	85.511
4	0.907	15.486	84.514
5	0.909	15.736	84.264
6	0.909	15.719	84.281
7	0.910	15.707	84.293
8	0.910	15.707	84.293
9	0.910	15.707	84.293
10	0.910	15.708	84.292

<b>Fable 4.19: Forecast Erro</b>	<sup>•</sup> Variance D	ecomposition f	or Diabetes cases
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# 4.3 Discussion of Results

The results of the study clearly revealed that both the diabetes and hypertension cases were asymmetric in nature. This lack of symmetry can be attributed to large swings in the datasets. The hypertension cases were platykurtic in nature indicating that the cases were widely distributed around their mean value whiles the diabetes cases were leptokurtic in nature indicating that the cases were closely distributed around their mean value. From the results, it was obvious that the diabetes cases were more volatile than the hypertension cases. In terms of variability of the cases, the diabetes cases have greater variability compared to the



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hypertension cases. This affirms how volatile the diabetes cases are than the hypertension cases.

The study clearly revealed that both the diabetes and hypertension cases exhibit trend in them. The log-linear trend model best represents the nature of trend characterising the diabetes and hypertension cases. The log-linear trend models revealed that for a unit change in time, the diabetes cases increase whiles the hypertension cases decreases. The log-linear trend models for both cases indicated that both cases have constant linear growth rate over time.

A unit root test conducted to investigate the stationarity of both the diabetes and hypertension cases clearly revealed that both cases were not stationary. This was affirmed by the time series plots of both cases and the ACF and PACF plots of both cases. The series were then transformed logarithmically and first differenced. From the results, the ADF test revealed that the transformed first differenced series were both stationary. The stationary series were then used to investigate the dynamic relationship between the diabetes and hypertension cases.

Before fitting the VAR model to the transformed stationary series, four model selection criteria were used to investigate the appropriate order of the VAR model. From the results, the BIC selected lag 1 while the FPE, AIC and HQIC selected lag 2. Both VAR (1) and VAR (2) model were fitted to the transformed datasets and the LRT used to select the best model. The results of the LRT revealed that the VAR (2) model best fits the datasets, thus the parameters of the VAR (2) model were estimated. From the results, it was obvious that there exist a



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dynamic relationship between diabetes and hypertension cases. This confirms the findings of Benard et al (2008), Tai et al (1991) and Epstein (1997) that diabetes and hypertension are interrelated diseases. The lag1 of diabetes was useful in predicting both diabetes and hypertension cases whiles lag 2 of both diabetes and hypertension were useful in predicting diabetes cases. Also, lag 1 of hypertension was useful in predicting hypertension cases. The significance of the lag values of both cases in predicting each other affirms the existence of dynamic relationship between the diabetes and hypertension cases. In order to make inference with the model, various diagnostic techniques were employed on the model to investigate the adequacy of the model. Both the univariate and multivariate Ljung-Box test revealed that the model was free from serial correlation whiles the univariate and multivariate ARCH-LM test also revealed that the model was free from conditional heteroscedasticity. The stability of the model parameters were also investigated using the eigenvalues and CUSUM test. Both test revealed that the model parameters were structurally stable, indicating that the residuals of the individual models in the VAR (2) model have zero mean and constant variance. The Jarque-Bera (JB) test indicated that the normality assumption of the VAR (2) model was satisfied.

The Granger causality test was used to investigate the nature of the relationship between the diabetes and the hypertension cases. The results revealed that the diabetes cases granger cause the hypertension cases but the reverse is not true, showing that there is a unidirectional relationship between the diabetes and the hypertension cases. This implies that if the previous values of diabetes cases are

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known, then future values of hypertension cases can be predicted. This result could also imply that if someone has a diabetes history then is likely the person would be suffering from hypertension but the reverse is not true. The instantaneous causality test revealed that diabetes causes hypertension and hypertension causes diabetes, indicating a bilateral relationship between diabetes and hypertension. This affirms the fact that a person with hypertension is likely to be suffering from diabetes and vice versa.

Furthermore, an impulse response analysis performed to investigated how the diabetes and hypertension cases in the VAR (2) model interact following a shock in the VAR (2) model revealed the existence of relationship between the hypertension and the diabetes cases. The FEVD also affirms that there exists a relationship between the diabetes and hypertension cases. For instance in the tenth period, about 91.53% of the forecast uncertainty in hypertension was explained by innovations in hypertension, whiles about 8.47% of the forecast uncertainties in hypertension have been explained by diabetes cases. Also, in the tenth period the diabetes cases explained about 84.29% of the forecast uncertainty in diabetes cases uncertainty in diabetes cases.

The VAR (2) model and the various inferential procedures applied on it clearly revealed that there exists a short run relationship between the diabetes and the hypertension cases. The findings have revealed that a person with hypertension history is likely to have diabetes since the lag 1 value of diabetes can be used to predict hypertension cases. Also, a person with diabetes history is likely to have



hypertension since lag 2 value of hypertension can be used to predict diabetes cases. These findings were supported by the causality test, impulse response analysis and FEVD.

# **4.4** Conclusion

This chapter focused on the analyses and discussion of the results obtained. It gave a detailed and concise presentation of the major finding of the study.



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# CHAPTER FIVE CONCLUSION AND RECOMMENDATIONS

#### **5.0 Introduction**

This chapter presents the conclusion and recommendations of the study.

## **5.1 Conclusion**

In this study, the monthly cases of diabetes and hypertension from January, 2006 to December, 2014 were studied. Before investigating the dynamic relationship between diabetes and hypertension cases, the monthly characteristics of both series were explored. The results revealed that both series were asymmetric in nature due to large swings in the datasets. An exploration of the nature of trend characterising both series revealed that the nature of trend in both diabetes and hypertension cases were best modeled by the log-linear trend model. However, the results revealed that for a unit change in time the diabetes cases increases whiles the hypertension cases decreases.

The diagnostic tests revealed that the VAR (2) model fitted to investigate the dynamic relationship between the diabetes and hypertension cases was adequate. The VAR (2) model was then used to make inference about the relationship between diabetes and hypertension cases. The Granger causality test revealed a unidirectional relationship between diabetes and hypertension whiles the instantaneous causality test revealed a bilateral relationship between diabetes and hypertension. This result implies that a person with hypertension history is likely to suffer from diabetes and vice versa. The impulse response analysis and forecast



error variance decomposition analysis both affirm that there exist a dynamic relationship between diabetes and hypertension.

Although, all diagnostic techniques employed revealed that the VAR (2) model is adequate, sole reliance on this model for investigating the dynamic relationship between diabetes and hypertension cases is not advisable. Therefore continuous monitoring of the performance of this model is required to make the use of this model more realistic.

## **5.2 Recommendations**

Following the outcome of this research work, the following recommendations were made;

The results revealed that there is a causal relationship between diabetes and hypertension cases. It is therefore recommended that the Ministry of Health (MoH), public health workers and other stakeholders in the health sector should come together to educate the public on how these risk factors of cardiovascular diseases interrelates, their consequences and the need to report to a medical facility if they detect any signs of these diseases.

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The log-linear trend model showed a decreasing pattern in the number of hypertension cases for a unit change in time. This decreasing pattern does not guarantee public health workers to infer that the hypertension cases are not prevalent. Rather it is recommended that the MoH should liaise with health workers to provide intensive education on some



dangers of hypertension and the need to seek for early treatment in any nearby medical facility.

iii. This study investigated the short run relationship between diabetes and hypertension cases using Vector Autoregressive model, it is therefore recommended that further studies should be carried out on the long run relationship between diabetes and hypertension using Vector Error Correction (VEC) model and the results compared to see which of these models best explains the dynamic relationship between diabetes and hypertension cases.

iv.

It is also recommended that the MoH advices the heads of the various teaching hospitals in the country to make data on the risk factors of cardiovascular diseases readily available. This will make it possible for researchers to study the dynamic relationship among the several risk factors of cardiovascular diseases.



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## REFERENCES

- Abdulsalam, S., Olugbenga-Bello, A., Olarewaju, O. and Abdus-salam, I. (2014).
  Sociodemographic Correlates of Modifiable Risk Factors for Hypertension in a Rural Local Government Area of Oyo State South West Nigeria. *International Journal of Hypertension*, 2014:1-9.
- Aboagye-Sarfo, P., Oduro, F. T. and Okyere G. A. (2013). Time Series Forecast of New HIV Cases in the Ashanti Region of Ghana. International Journal of Scientific and Engineering Research, 4(5):546-549.
- Addo, J., Albert, G., B., A. and Koram, K., A. (2006). The changing pattern of hypertension in Ghana: A study of four rural communities in the Ga District. Ethnicity and disease, 16: 894-899.
- Aekplakorn, W., Chariyalertsak, S., Kessomboon, P., Sangthong, R. and Inthawong, R. (2011). Prevalence and Management of Diabetes and Metabolic Risk Factors in Thai Adults. *Diabetes Care*, 34: 1980-1985.
- Agyemang, C. (2006). Rural and urban differences in blood pressure and hypertension in Ghana, West Africa. *Public Health*, **120**: 525-533.
- Akaike, H., (1974). A New Look at the Statistical Model Identification. *IEEE Translation on Automatic Control*, AC-19:716-723.
- Alberto, G. E., Angel, O., Michel, V. H., and Armando, A. J. (2007). Forecasting malaria incidence based on monthly cases reported and environmental factors in Karuzi; Burundi, 1997-2003. *Malaria Journal*, 6(129):1-10.



- Amoah, A. G. B., Samuel K. O., and Samuel, A. (2002). Diabetes in Ghana: a community based prevalence study in Greater Accra. *Diabetes Research* and clinical Practice, 56 (3): 197–205.
- Amoah, A., Owusu, S., and Adjei, S. (2002). Diabetes in Ghana; A community based prevalence study in Greater Accra. Diabetes Research and Clinical Practice, 56 (3): 197-205.

STUDIES

UNIVERSITY FOR DEVELOPMENT

- Amoah, A.G. (2003). Hypertension in Ghana: a cross sectional community prevalence study in Greater Accra. *Summer*, 13(3):310-3115.
- Amos, F. D., Niya, W., Laurencia, H. R., David, A., and Easmon, O. (2013). Prevalence and Risk Factors for Hypertension in Adansi South, Ghana. Sage open journal, 3(5): 1-5.
- Arauz-Pacheco, C., Parrott, M. A., and Raskin, P. (2002). The treatment of hypertension in adult patients with diabetes. *Diabetes Care*, 25(1): 134– 147.
- Athanasakis, K., Souliotis, K., Tountas, Y., Yantopoulos, J., Kyriopoulos, J., and Hatzakis, A. (2014). A Short-Term Cost-Effectiveness Analysis of Hypertension Treatment in Greece. *Hellenic Journal of* Cardiology,55(3): 197-203.
- Benin, C-L and Essuman, A. (2014). Evaluating the effectiveness of blood pressure treatment in mild to moderate hypertension at the Korle-Bu polyclinic, Accra. *Postgraduate Medical Journal of Ghana*: 3(1):1-6.
- Bernard, M.Y. C., Nelson, M.S. W., Annette, W.K. T., Sidney T., Neil Thomas, G., Gabriel, M. L., Hung, F. T., Jean, W., Edward, D. J.,

Chu, P. L., Tai, H. L., and Karen, S.L. L. (2008). Association between raised blood pressure and dysglycemia in Hong Kong Chinese. *Diabetes Care*, **31**(9):1889-1891.

- Bin-Lu, Yang, Z., Wang, M., Zhen, Y., Gong, W., Yang, Y., Wen, J., Zhang, Z., Zhao, N., Zhu, X. and Hu, R. (2010). High prevalence of diabetic neuropathy in population-based patients diagnosed with type 2 diabetes in the Shanghai downtown. *Diabetes Research and Clinical Practice*, 88 (2010): 289-294.
- Box, G. E., and Jenkins, G. M., (1976). Time Series Analysis Forecasting and Control. Holden-Day, San-Francisco.
- Brown, R. L., Durbin, L., and Evans, J. M., (1975). Techniques for Testing the Consistency of Regression Relationships over time. *Journal of the Royal Statistical Society*, Series B 37: 149-192.
- Burket, B., A. (2006). Blood pressure survey in two communities in the Volta Region, Ghana, West Africa, *Ethnicity and disease*. **16**(1): 292-294.
- Campbell, R. C. M., Gilbert, E. R., Leiter, A. L., Larochelle, P., Tobe, S., Chockalingam, A., Ward, R., Morris, D., Tsuyuki, T. and Harris, B. S. (2011). Hypertension in People with Type 2 Diabetes. *Canadian Family Physician Journal*, 57(9):997-1002.
- Cappucio, F., P., Micah, F.,B., Emmer, L., Kerry, S., M., Antwi, S., Martin-Peprah, R., Phillips, R., O., Plange-Rhule, J. and John, B., E. (2004).
  Prevalence, Detection, Management and Control of Hypertension in Ashanti, West Africa. *Hypertension*, 43(5): 1017-1022.

UNIVERSITY FOR DEVELOPMENT STUDIES

÷



- Catherine, C. C., Keith, F. R., Danita, D. B-H., Mark, S. E., Katherine, M. F., Michael, M. E., Sharon, H. S., Desmond, E. W., Linda, S. G., and Edward, W. G. (2006). Prevalence of Diabetes and Impaired Fasting Glucose in Adults in the U.S. Population National Health and Nutrition Examination Survey 1999–2002. *Diabetes Care*. 29(6):1263-1268.
- Chobanian A. V., Bakris G. L, Black H. R, Cushman W.C, Green, L. A., Izzo J.
  L. Jr, Jones, D.W., Materson, B. J., Oparil, S., Wright, J. T. Jr., and
  Roccella E.J. (2003). The seventh report of the Joint National
  Committee on Prevention, Detection, Evaluation, and Treatment of High
  Blood Pressure. Journal of Hypertension, 42(6): 1206–1255.
- Danquah, I., George, B-A., Terpe, K-P., Frank, M., Yaw, A., A., Ekkehart, D., Markus, V., G., Joachim, S. and Frank, P., M. (2012). Diabetes mellitus type 2 in Urban Ghana: Characteristics and associated factors, BMC Public Health, 12(210): 1-8.
- Deepa, R., Shanthirani, C. S., Pradeepa, R., and Mohan V., (2003). Is the 'Rule of Halves' in Hypertension Still Valid? - Evidence from the Chennai Urban Population Study Gopalapuram, Chennai, India, Journal of Association of physicians of India, 51:153-157.
- Dickey, D. A., and Fuller, W. A., (1979). Distribution of the Estimators for Autoregressive Time Series with a Unit-root. Journal of American Statistical Association, 74 (366): 427-431.

- Dorherty, S., T. and Graves, S., P. (2015). Time-Series Analysis of Continuously Monitored Blood Glucose: The Impact of Geographic and Daily Lifestyle Factors. Journal of Diabetes Research, 2015: 1-6.
- EI Elamin, A., Fauzia, R., Alaaeldin, M. K. B., and Suada, A. M. (2015). A Prospective Study Comparing the Effects of Ramadan Fasting on Metabolic Parameters in Healthy Muslims from Three Different Nationalities in Dubai. *Journal of Diabetes and Metabolism*, 6(1):1-5.
- Ekezie, D. D., Opara, J., and Okenwe, I. (2014). Modelling and Forecasting Malaria Mortality Rate using SARIMA Models A Case Study of Aboh Mbaise General Hospital, Imo State Nigeria. Science Journal of Applied Mathematics and Statistics, 2(1): 31-41.
- Engle, R. F., (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, 50 (4): 987-1007.
- Epstein, M. (1997). Diabetes and Hypertension: the bad companions. Journal of Hypertension, 15(2):55-62.
- Erhun, W.O., Olayiwola, G., Agbani, E.O and Omotoso, N.S., (2005). Prevalence of Hypertension in a University Community in South West Nigeria. *African Journal of Biomedical Research*, 8(1): 15-19.

Gelper, S., and Croux, C., (2007). Multivariate Out-of-Sample Tests for Granger Causality. Computational Statistics and Data Analysis, 51 (7): 3319-3329.

Ghorbani A. (2013). Best Herbs for Managing Diabetes: A Review of Clinical Studies. *Brazilian Journal of Pharmaceutical Sciences*, **49**(3):413-422.

5



- Global Health Observatory (GHO). (2012). Raised Blood pressure, http://www.who.int/gho/ncd/risk factors/blood pressure prevalence text/en/index.html 20/04/2015.
- Gress, T. W., Nieto, F. J., Shahar, E., Woffod, M.R., and Brancati F.L. (2000).
  Hypertension and antihypertensive therapy as risk factors for type 2
  diabetes mellitus. Atherosclerosis Risk in Communities Study. *The New England Journal of Medicine*, 342 (13):905-912.
- Gujurati, D. N., (2003). Basic Econometrics. Fourth Edition. New Delhi, the McGraw-Hill Co.
- Hannan, E. and Quinn, B., (1979). The Determination of the Order of an Autoregression. J. Roy. Statist. Soc. Ser. B 41: 190–195.
- Harris, M., Flegal, K. M., Cowie, C. C., Eberhardt, M. S., Goldstein, D. E., Little,
  R. R., Wiedmeyer, H. M., and Byrd, D, D. (1998). Prevalence of diabetes, impaired fasting glucose, and impaired glucose tolerance in U.S. adults. The Third National Health and Nutrition Examination Survey, 1988-1994. *Diabetes Care*. 21(4):518-524.
- Karim, A., Jabali, E., L. and Alousi, S., L. (2003). Identification of two time series models of type 1 diabetes using patient's clinical database. *Pakistan Journal of Applied Sciences*, 3(4): 274-279.
- Kartharina, W.M., Richard, S.C., Jose R. B., Simona G., Hans-Werner H.,Michel J., Mika K. N. P, Fernando, R. A., Birgitta S., Michael T. D. V.,and Fenicia V. (2003). Hypertension prevalence and Blood Pressure

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Levels in 6 European Countries, Canada and the United States. The Journal of the American Medical Association, **289**(18):2363-2369.

- Kearney, P. M., Whelton, M., Reynolds, K., Muntner, P., Whelton, P. K., and He, J. (2005). Global burden of hypertension: analysis of worldwide data, *Lancet*, 365(9455):217-223.
- Keita, F., Naoyuki, H., and Kenjiro, K. (2005). Cost-Effectiveness Analysis of Hypertension Treatment: Controlled Release Nifedipine and Candesartan Low-Dose Combination Therapy in Patients with Essential Hypertension—The Nifedipine and Candesartan Combination (NICE-Combi) Study. *Hypertension Research*, 28(7):585-591.
- King, H., Aubert, R. E., Herman, W. H., (1998). Global burden of diabetes, 1995–2025: prevalence numerical estimates, and projections. *Diabetes Care*, 21(9):1414–1431.
- Kumar, V., Singh, A., Adhikary, M., Daral, S., Khokhar, A., and Singh, S. (2014).
   Seasonality of Tuberculosis in Delhi, India: A Time Series Analysis.
   Tuberculosis research and treatment, 2014:1-5.
- Landsberg, L., Molitch, M. (2004). Diabetes and hypertension: pathogenesis, prevention and treatment. *Clinical and Experimental Hypertension*, **26**:621-628.
- Ljung, G. M., and Box, G. E., (1978). On the Measure of Lack of Fit in Time Series Models. *Biometrika*, 65 (2):297-303.
- Lutkepohl, H., (2005). New introduction to Multiple Time Series Analysis. Springer

STUDIES

UNIVERSIT

- Luz P. M., Mendes, B. V., Codeço, C. T., Struchiner, C. J., Galvani, A., P.(2008). Time series analysis of dengue incidence in Rio de Janeiro, Brazil. The American Journal of Tropical Medicine and Hygiene, 79(6):933-939.
- Maguy, C., Mario, N., and Edgar, G. C. (2012). Diabetes and Coronary Heart Disease: A Risk Factor for the Global Epidemic. International Journal of Hypertension, 2012:1-7.
- McLarty D .G., Swai, A. B., Kitange, H. M., Masuki, G., Mtinangi, B.,
  L., Kilima, P. M., Makene, W. J., Chuwa, L. M., and
  Alberti, K. G. (1989). Prevalence of diabetes and impaired glucose tolerance in rural Tanzania. *Lancet.* 1(8643):871-875.
- Mevlut, T., and Imran, K. (2006). Comparison of four different time series methods to forecast hepatitis A virus infections. *Expert Systems with Applications*, **31** (1):41-46.
- Myriam, G., Philippe, Q., Joël, G., Sylvie, C., Guy, L. R., Laurent, G., and Laurence, M. (2011). Time Series Analysis Of Dengue Incidence In Guadeloupe, French West Indies: Forecasting Models Using Climate Variables As Predictors. BMC Infectious Diseases, 11(166):1-33.
- Nemesure, B., Wu, S., Hennis, A., Leske C. M. (2006): studied Hypertension, Type 2 Diabetes, and Blood Groups in a Population of African Ancestry. *Ethnicity and Disease*, **16**:822-829.



STUDIES

ELOPMENT

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UNIVERSIT

- Nwafor, A. and Owhoji, A. (2001). Prevalence of diabetes mellitus among Nigerians in Port Harcourt Correlates with Social-Economic Status. Journal of Applied Sciences and Environmental Management, 5(1):75-77.
- Ogunleye, O. O., Ogundele, S. O., Akinyemi, J. O., Ogbera, O. A. (2012).
  Clustering of hypertension, diabetes mellitus and dyslipidemia in a Nigerian population: a cross sectional study. *African Journal of Medicine and Medical Sciences*, 41(2): 191–195.
- Okoduwa, S. I. R., Umar, A. I., Ibrahim, S., Bello, F. (2013). Relationship of oxidative stress with type 2 diabetes and hypertension. Journal of Diabetology, 1(2):1-10.
- Olatunbosu, S. T., Ojo, P. O., Fineberg, N. S., and Bella, A. F. (1998). Prevalence of diabetes mellitus and impaired glucose tolerance in a group of urban adults in Nigeria. *Journal of the National Medical Association*, **90**(5):293-301.
- Olatunbosun, S. T., Ojo, P. O., Fineberg, N. S., and Bella, A. F. (1998). Prevalence of diabetes mellitus and impaired glucose tolerance in a group of urban adults in Nigeria. *Journal of the National Medical Association*, **90**(5): 293–301.
- Oldroyd, J., Banerjee, M., Heald, A., Cruickshank, K. (2005) Diabetes and ethnic minorities. *Postgraduate Medical Journal*, **81**(958): 486–490.
- Omar, M. A. K., Seedat, M. A., Dyer, R. B. and Motala, A. A. (1988). Diabetes and hypertension in South African Indians. South African Medical Journal, 73:635-637.

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UNIVERSITY FOR DEVELOPMENT STUDIES

- Otieno, C. F., Vaghela, V., Mwendwa, F. W., Kayima, J. K., and Ogola, E. N. (2005). Cardiovascular risk factors in patients with type 2 diabetes mellitus in Kenya: levels of control attained at the outpatient diabetic Clinic of Kenyatta National Hospital, Nairobi. *East African Medical Journal*, 82(12): 184–190.
- Ozlem, U., and Nimet, O. (2010). Relationship between diabetes mellitus, hypertension and obesity, and health-related quality of life in Gaziantep, a central south-eastern city in Turkey. *Journal of clinical nursing*, **19**(17): 2511-2519.
- Patricia, M. K., Megan, W., Kristi, R., Paul, K. W., Jiang H. (2004). Worldwide prevalence of hypertension: a systematic review. Journal of Hypertension, 22(1): 11-19.
- Ploberger, W., Krammer, W., and Kontrus, K., (1989). A New Test for Structural Stability in the Linear Regression Model. *Journal of Econometrics*, 40:307-318.
- Poljičanin, T., Ajduković, D., Šekerija, M., Pibernik-Okanović, M., Metelko, Z.,
  Mavrinac, V. G. (2010): Diabetes mellitus and hypertension have comparable adverse effects on health-related quality of life. *BMC Public Health Journal*, 10(12):1-6.
- Qi Li, Na-na, G., Zhan-Ying, H., Yan-Bo, Z., Shun-Xiang, Q., Yong-Gang, X., Ya-Mei, W., Xu, H. and Ying-Ying, L. (2012). Application of an Autoregressive Integrated Moving Average Model for Predicting the

27

STUDIES

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Incidence of Hemorrhagic Fever with Renal Syndrome. *The American* Journal of Tropical Medicine and Hygiene, 87(2):364-370.

- Schwarz, G. E., (1978). Estimating the Dimension of a Model. Annals of Statistics, 6:461-464.
- Sowers, J. R., Epstein, M., Frohlich, E. D. (2001). Diabetes, hypertension, and cardiovascular disease an update, *Hypertension*, **37**(4): 1053–1059.
- Stamler, J., Vaccaro, O.,. Neaton, J. D., Wentworth, D. (1993). Diabetes, other risk factors, and 12-year cardiovascular mortality for men screened in the multiple risk factor intervention trial, *Diabetes Care*,16(2): 434–444
- Suleman, N. and Sarpong, S. (2011) Statistical modeling of hypertension cases in Navrongo, Ghana, West Africa. American Journal of Social and Management Sciences, 2 (4): 377-383.
- Sutapa, A. (2014). Frequency of Food Consumption and Self-reported Diabetes among Adult Men and Women in India: A Large Scale Nationally Representative Cross-sectional Study. Journal Diabetes and Metabolism, 6(1):1-11.
- Tai, T. Y., Chuang, L. M., Chen, C. J. and Lin, B. J. (1991). Link between Hypertension and Diabetes Mellitus Epidemiological Study of Chinese Adults in Taiwan. *Diabetes care*, 14(11): 1013-1020.
- Tatsuya, S., Yoshiki, N., Yoshinori, Y., Hiroaki, I., Haruhiko, A., Hidenori, A.,
  Susumu, H., Hirokazu, K., Daisuke, M., and Kunio, M. (2007).
  Comparison of the Effects of Telmisartan and Olmesartan on Home
  Blood Pressure, Glucose, and Lipid Profiles in Patients with

Hypertension, Chronic Heart Failure, and Metabolic Syndrome. Hypertension Research, **31**(5):921-929.

Trojak A. (2014). Nonalcoholic Fatty Liver Disease in Patients with Type 2
 Diabetes (NAFLD) - Gender Differentiation in Determinants. Journal of
 Diabetes and Metabolism, 6(1):1-3.

Varun, K., Abha, M., Sanjeet, P., Greeta, Y., Richa, T., Deepak, R., and Saudan,
S. (2014). Forecasting Malaria Cases Using Climatic Factors in Delhi,
India: A Time Series Analysis. *Malaria Research and Treatment*, 2014:16.

WHO (2015). Report on cardiovascular diseases.

- Wild, S., Roglic, G., Green, A., Sicree, R., and King H. (2004). Global prevalence of diabetes: estimates for the year 2000 and projections for 2030. *Diabetes Care*, 27(5):1047-1055.
- William, A. P., Mitchell, B. C., Maria, T. K. and Evgeny, A. (2013). The effects of the 2006 Russian Alcohol- Related Mortality: An Interrupted Time Series Analysis. *Alcoholism Clinical and Experimental Research*, 38(1):257-266.
- Yancy, Jr. S. W., Foy, M., Chalecki, M. A., Vernon, C. R., and Eric, C., Westman, C. E. (2005). A low-carbohydrate, ketogenic diet to treat type 2 diabetes. *Journal of Nutrition and Metabolism*, 2(34): 1-7.

Yury, E. R. (2011). Alcohol Consumption and Suicide Rates in Russia. Suicidology online Open Access Journal: 267-274.



- Ziyyat, A., Ramdani, N., Bouanani, E. N., Vanderpas, J., Hassani, B., Boutayeb,
  B., Aziz, M., Mekhfi, M., Bnouham, M., and Legssyer, A. (2014).
  Epidemiology of Hypertension and its Relationship with Type 2
  Diabetes and Obesity in Eastern Morocco. Springer Open Journal, 3(644):1-7.
- Zuleat, M. O. (2007). The incidence of hypertension among a select population of adults in the Niger Delta Region of Nigeria. *The Southeast Asian journal* of tropical medicine and public health, **38**(5):947-949.

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